PERFORMANCE PREDICTION OF A HYDROCARBON RESERVOIR BY HISTORY MATCHING USING GENETIC ALGORITHM (NSGA-II)

A thesis submitted to the
University of Petroleum and Energy Studies

For the award of
Doctor of Philosophy
In
Chemical Engineering

BY
Giridhar Vadicharla

July 2023

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DECLARATION

I declare that the thesis entitled '*Performance prediction of a Hydrocarbon reservoir by History matching using Genetic Algorithm (NSGA-II)*' has been prepared by me under the guidance of Dr. Santosh K. Gupta, Dr. Pushpa Sharma and Dr. Deoki N. Saraf. No part of this Thesis has formed the basis for the award of any degree or fellowship previously.

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Date: 07/07/2023

THESIS COMPLETION CERTIFICATE

This is to certify that the thesis entitled "**Performance prediction of a Hydrocarbon Reservoir by History Matching using Genetic Algorithm (NSGA-II)**" by Giridhar Vadicharla, in partial completion of the requirements of the Award of DOCTOR OF PHILOSOPHY in Chemical Engineering is an original work carried by him under my supervision and guidance.

It is certified that the work has not been submitted anywhere else for the award of any other diploma or degree of this or any other University.

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(Giridhar Vadicharla)

This Thesis is dedicated to eternal love of my life

My dear parents – Laxminarayana & Nirmala

and

My beloved Geetha Radhika & Koushikivalli

EXECUTIVE SUMMARY

History matching of hydrocarbon reservoirs essentially requires the development of accurate reservoir models that represent the actual reservoirs. Building a reliable numerical reservoir model incorporating all the geological, geophysical, geochemical and petrophysical data of the reservoir available through the petroleum exploration process is not an easy task, owing to it being highly non-linear and heterogeneous. Once a geological model of a reservoir is developed with spatial distribution of rock properties (like porosity and permeability), a flow model needs to be developed which can estimate the multi-phase flows of oil, water and gas through the flow channels into the well. Here, dynamic rock and fluid properties such as relative permeabilities, fluid saturations, etc., become important in addition to the initial and boundary conditions of the reservoir. There are several commercial numerical simulators, viz., CMG® (CMG Ltd., Calgary, Canada), ECLIPSE (Schlumberger LTD), JewelSuiteTM (Baker Hughes, Houston, Texas), etc., which can forecast the rates of production of oil, gas and water along with bottom hole flowing pressure in each well, provided all the required inputs are available. However, the static rock properties such as permeability and porosity are only available at well locations (exploratory or production wells) and there is no reasonable way to find how these vary between the wells and in the rest of the reservoir.

Genetic Algorithm (GA) is an evolutionary algorithm based on Darwin's principle of 'survival of the fittest' and inspired from genetics. NSGA-II, a variant of Genetic Algorithm, is applied to the problem of history matching in this study, for estimating the permeability distribution in the reservoir. Initially, the technique is applied to a synthetic reservoir and is validated. It is then applied to a real reservoir problem to find multiple distinct history matches and the accurate reservoir model is chosen for predicting the performance of the reservoir in the future. The larger number of variables were reduced using the pilot point method, and Sequential Gaussian Simulation (SGSIM, a geostatistical non-linear interpolation technique)

was applied to estimate the neighboring variables. The reduced number of variables are optimized using NSGA-II. The combined application of SGSIM and NSGA-II for solving the problem of history matching has not been explored before. The study successfully establishes the application of NSGA-II as one of the promising optimization techniques for history matching which yields better reservoir models which can be used for performance prediction and production optimization.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

BHP	Bottom Hole flowing Pressure	Kg/cm^2, psia
GOR	Gas-oil ratio	v/v
NDF	Non-dominated front in the population	
WC	Watercut	
A	Cross-sectional area normal to flow	m^2, ft^2
a, b	Individuals of population 'P'	
B	Formation Volume Factor	
C_f	Compressibility	cm^2/kg, $psia^{-1}$
d^O	Observed filed data	
d^S	Simulated model output	
f_m^{max} , f_m^{min}	Maximum and minimum fitness value of m^{th} objective function	
h	Hydraulic pressure head	ft, m
k	Permeability	mD, m^2
k_r	Relative permeability	
L	Length of porous domain	m
$\dot{m}_{cx}$	Mass flux of component 'c' in x direction	$kg/m^2.s$
N_q	Total number of months for which fluid production data is used	
N_w	Total number of wells	
P	Pressure	Kg/cm^2, bar
P_C	Capillary pressure	Kg/cm^2, psia
P_c	Crossover probability	
P_m	Mutation probability	
P_{nw}	Pressure in non-wetting phase	Kg/cm^2, psia
P_w	Pressure in wetting phase	Kg/cm^2, psia
Q	Objective function	
q_x	Flow rate in x-direction	m^3/day
R_{so}	Solubility of gas in oil	m^3/m^3, SCF/STB
S	Fluid Saturation	
S_o, S_g, S_w	Fractional Saturation of oil, gas and water	
t	Time	seconds
u	Darcy velocity	m/s, ft/s
V	Volume	m^3, ft^3
x	Spatial variable in x direction	m, ft
ΔP	Pressure change	Kg/cm^2, psia
Δt	Time step	seconds
Δx	Spatial step size in x direction	m, ft
φ	Porosity	
μ	Fluid viscosity	cP
λ	Mobility of fluid phase	mD/kg
ρ	Density	kg/m^3
ρ_{csc}	Density of component 'c' at standard conditions	kg/m^3

$\emptyset$	Fluid potential	Kg/cm^2, psia

Subscripts

o, g, w	Oil, gas and water phase	
T	Reservoir temperature	K

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW AND MOTIVATION

Petroleum, often referred to as the 'black gold', is a natural energy source from the subsurface. Since decades, more than half of the energy supplies to the world are from petroleum and this is likely to continue since the contribution of renewable energy to the global needs is not expanding rapidly enough. Huge investments in terms of money, time and technology are made by oil and gas industries for efficient exploration and exploitation of petroleum reserves.

Hydrocarbon reservoirs have oil, gas and water entrapped in core and it needs to drill exploratory wells, as shown in Fig. 1.1, to get the core samples and estimate the oil reserves. Production wells are later drilled to start the production subjected to economic exploitability of the reserve.

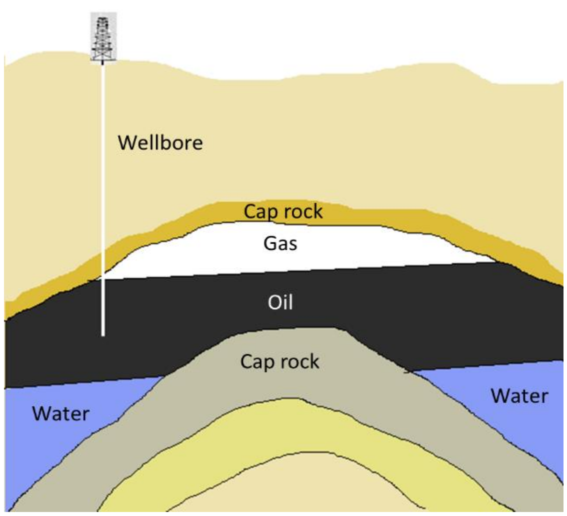


Figure 1.1: Schematic of a Hydrocarbon reservoir

After drilling, workover is any operation done, or within, or through the wellbore after the initial completion. During lifetime of every well, several workovers may be required to fulfil the very purpose of well satisfactorily. However, proper drilling, cementing and completion practices minimizes the need of workover.

Well completion is the process of making a well ready for production after drilling operations. Artificial lift generally describes various technologies used to increase the flow of liquids within a production well. When the natural drive energy of the reservoir is not strong enough to push the oil to the surface, artificial lift is employed to recover more production. Hydraulic pumping systems, electrical submersible pumps, rod pumps, subsurface pumping, gas lift are some of the artificial lift technologies.

Recovery of hydrocarbons from hydrocarbon reservoir commonly occurs in several recovery stages viz. primary recovery, secondary recovery and tertiary recoveries (Enhanced oil recovery). Primary recovery is the recovery of hydrocarbons from the reservoir using the natural energy of the reservoir as a drive. Solution-gas drive, gas-cap drive, natural water drive, reservoir compaction and gravity drainage come under primary recovery. Secondary recovery results from the augmentation of natural energy through injection of water or gas to displace oil toward producing wells. Tertiary recovery or enhanced oil recovery is an oil recovery enhancement method using sophisticated techniques that alter the original properties of oil. This include chemical flooding (alkali, polymer flooding), thermal recovery (steam flooding), miscible displacement (CO_2 injection).

Reservoir modeling, simulation and production forecasting play a key role in field development effectively and consequently in management and strategies under various operating and maintenance scenarios. Production from a reservoir cannot be estimated accurately in terms of production from each well, cumulative production and the duration of production. This defines how a development of reservoir should be done. Though no information is available initially about the production, wells are drilled and production is started. Only after more than 5 years of production, production data or history of production will be available. This enables to create a better model of the reservoir. More the history of production, better the model. In general, simulation aims to construct a consistent numerical model that resembles the real physics happening inside a system. Reservoir flow simulation aims at building a model that characterize the flow of fluids in the actual reservoir in terms of its geological, petrophysical, and geochemical properties. Owing to the heterogeneity of a reservoir, it is indeed a difficult task building a consistent geological reservoir model that replicates all the geological realism available through the petroleum exploration process. In addition, the geological and petrophysical data obtained from the production and exploration wells represent only a minute area, when compared to the total volume of reservoir. Moreover, spatial variation of these rock properties (porosity and permeability) is highly unpredictable and it is not a quite easy task to obtain accurate estimates of these [1]. The most challenging part is that how these spatial properties are distributed in the vast volume of the reservoir is clueless.

Despite these challenges, reservoir engineers always attempt to construct models that approximate geological practicality and reproduce historical field observations when simulated. It is vivid that a reliable reservoir model assures confidence in production forecast and can be used to understand the reservoir‘s behavior for present and to predict the future, under various operating scenarios such as workover, well completion and artificial lift strategies etc., as described above. Exhaustive understanding of reservoir behavior is necessary for efficient and optimal future field development plans such as optimizing the surface facilities, well locations and recovery strategies (primary, secondary and tertiary). Hence, for effectively predicting the performance of a reservoir, a geological model with well-established rock and fluid properties needs to be developed. However, one wonders is it possible to predict oil production without going through an elaborate exercise of modeling and simulation which is expensive and time consuming. Artificial intelligence which is making a paradigm shift in almost all spheres of human activity, and more specifically, Genetic Algorithm (GA) appear to be promising tools for such an attempt.

The numerical reservoir models consist of highly nonlinear partial differential equations (PDEs) with both time and space as independent variables. The solution of these equations require initial and boundary conditions which are generally complex in petroleum reservoirs. These PDEs describe the hydrodynamic fluid flow within the reservoir system along with mass transfer process, which is expressed as a function of fluid properties (viscosities, PVT properties, etc.), spatially varying rock properties (permeability and porosity) and rock-fluid interaction properties (fluid saturations, connate water saturation, relative permeabilities, etc.). Several commercial numerical simulators available divide the entire reservoir into several thousands of three dimensional grid blocks and numerically integrate the flow equations to find the solution. However, most of these properties, particularly the rock properties are not available except at well locations. Though a few correlations are available for estimating relative permeabilities, there is no way to estimate rock properties between wells and rest of the reservoir as they vary unpredictably in space [2]. Hence, reservoir simulation cannot be used directly to find the field production profile in absence of requite information.

History matching is one technique to salvage this scenario where one targets to find all the missing information such that when used with the numerical simulator, the output will match with the field observations which are typically production of oil, gas and bottom hole flowing pressure. It is really essential because the development of field, number of wells required and their location, expectation and duration of these wells depend on how effective history matching is done. Secondary recovery also may be attempted depending on how efficient the reservoir model generated is, by matching history accurately. Initially, manual trial and error procedures are attempted to adjust these parameters and then verify if the predictions match with field observations. This is extremely tedious and time consuming and was the only way to find the critical properties such as porosity and permeability [3]. The reservoirs being highly heterogeneous, these properties were assigned grid-block-wise and adjusted until a satisfactory match was obtained. History matching a complex reservoir with large number of wells used to consume months of human time, if done manually. It is obvious that two individuals attempting to history match, claiming equally good match, can come with very different permeability maps for the same reservoir. Hence, history matching is an ill-defined problem and does not have a unique solution although modeling and simulation do provide a unique solution. The inverse problem, as history matching is usually referred to, can have infinitely many valid solutions [2].

All history-matching techniques proposed in the literature are based on the inverse modelling problem. Although the main aim of history-matching is minimization of the square of data mismatch, the methods that are used for minimization as well as for evaluating uncertainty vary broadly. After manual history-matching, evolutionary algorithms were developed to automate the history-matching. The automated approach is iterative and links optimization techniques to statistical analysis and obtains the suitable best parameter combination that results in good reservoir history matching. These algorithms are population-based optimization algorithms, mimicking processes happening in biological evolution. The optimization algorithm for minimizing the objective function for history-matching can be broadly divided into two categories, *viz*., gradient and non-gradient methods. Though the application of these techniques could solve the purpose of history matching which helps in characterizing the reservoir and evaluating uncertainties, each of them have their own limitations and are specific to certain case studies. Hence, an attempt is made to test the usage and efficacy of Non-dominated Sorting Genetic Algorithm – II (NSGA-II, a variant of Genetic Algorithm (GA) used for solving multi-objective problems) for history matching that achieves better convergence with minimum computational time.

GA is an optimization technique which is based on Darwin's 'survival of the fittest'. It is a computer-based search procedure inspired from genetics, which has widespread application. This process utilizes an initial population of individuals/solutions, known as chromosomes, which are further processed where they undergo inheritance, crossover and mutation for several generations to obtain potential solutions. The new generation chromosomes are evaluated based on a fitness function. This process continues until the algorithm converges to the potential solutions to the problem. The fitness function represents the individual chromosome fitness and is expressed by the objective function [4]. The best member of this 'final' population is taken to represent the optimal solution. Although GA finds only near-optimal solutions, for all practical purposes these are accepted as optimal. NSGA-II is one of the variants of genetic algorithm, which is exclusively used for minimization problems with more than one objective functions.

1.2 RESEARCH OBJECTIVES

- To develop a computer program, for history matching, that connects a commercial reservoir simulator with the NSGA-II MATLAB® code, which is capable of forecasting oil production based on available field observations for a single well and cumulative production from all the wells and perform history matching by comparing the predicted production with actual field production.
- To validate the above-developed history matching methodology and code using a synthetic 2D hydrocarbon reservoir with a known permeability distribution map.
- To match the production history of a real reservoir using the above-developed procedure.
- To reduce the number of iterated variables, which may help in reducing computational time, using pilot point method along with Sequential Gaussian Simulation (SGSIM) for non-linear interpolation to estimate the value of unknowns at original genetic algorithm points and compare the results.

1.3 RESEARCH METHODOLOGY

❖ Literature Survey:

An extensive literature survey on various optimization techniques that assist in automated history matching is carried out. After a thorough study of the advantages and limitations of these techniques, an attempt is made to check the usage and efficacy of NSGA-II, which has not been attempted earlier.

- Developing a mathematical model:

  A black oil model is generally used for modeling a petroleum reservoir, where each phase (oil, gas and water) is treated as a single component. In the black oil model, oil and water are considered to be immiscible while gas may exist as solution gas or free gas. The black oil model relies on the assumption that the reservoir fluids are in thermodynamic equilibrium through the reservoir and maintain constant reservoir temperature. A mathematical model has been developed for 2-D multiphase black oil model flow of fluids using the conservation of mass equation in conjunction with Darcy's velocity, fluid potentials and saturations of phases.

- Software tools and techniques:

  Multiple realizations of permeability models that are conditioned enough to available measurements from the wells are generated by algorithms presented in the geostatistical MATLAB® toolbox, 'mGstat'. In the current research, GSLIB's (Geostatistical Software LIBrary, Stanford Center for Reservoir Forecasting, Stanford University, USA) VISIM and SGeMS' (Stanford Geostatistical Modeling Software) SGSIM (Sequential Gaussian Simulation) packages are applied using the 'mGstat' interface. For flow modelling, a CMG simulator (CMG®-IMEX™) is used to get the production rates of oil, water and gas. The code for multi-objective optimization available in MATLAB®, is modified suiting to the need of history matching.

- Research Execution steps

  - A mathematical model for production of hydrocarbons from a hydrocarbon reservoir is developed for the black oil model.
  - Approximate distribution map of variables like porosity and permeability for the reservoir are generated using the geostatistical MATLAB® toolbox.
  - The porosity and permeability data are fed to the CMG® IMEX™ simulator that gives oil, gas and water production for the reservoir. For a given period of time, whose production data is available, the deviation between simulated

production data and actual production data is minimized with the application of NSGA-II.

- Initially, the methodology is tested for a 2D synthetic black oil reservoir and is validated against known data.
- After validation, the methodology is applied to a real 3D black oil reservoir.

1.4 THESIS OUTLINE

Chapter-1 provides the importance of reservoir production forecasting and history matching problem towards efficient and optimal field development. A brief introduction is provided to the adapted methodology used for automating the history matching process and production forecasting.

Chapter-2 offers extensive literature review on various optimization techniques and their application to production forecasting and history matching of a reservoir.

Chapter-3 discusses the numerical reservoir modeling and simulation approach used to compute the hydrodynamic fluid flow in the black-oil reservoir.

Chapter-4 discusses the details of genetic algorithm (GA) and its variant (NSGA-II) technique used as optimization tools to solve the history matching problem. This chapter also presents the application and validation of the NSGA-II technique for 2D synthetic reservoir history matching.

Chapter-5 provides the application of NSGA-II and NSGA-II coupled with the SGSIM techniques towards a 3D real reservoir history matching. This chapter also discusses the potential of the developed technique in predicting reservoir performance in the future.

Chapter-6 comprises the conclusions and recommendations for future work in the area of history matching with genetic algorithm.

CHAPTER 2

LITERATURE REVIEW

Reservoir modelling and forecasting production are crucial inputs to the efficient management of petroleum. Developing reliable numerical reservoir models which integrate all the geological, geochemical, geophysical, and petrophysical data of the reservoir available through the petroleum exploration process, can help alleviate this problem. As these reservoirs are extremely heterogeneous as well as nonlinear in nature, obtaining accurate estimate of the spatial distribution of reservoirs' properties that identifies the reservoir is quite difficult which influence corresponding production profiles. Petroleum engineers always pursue to construct reservoir models which are able to produce consistent production forecasts so that further reservoir development in terms of recovery strategies (primary, secondary and tertiary) to be employed, locating new wells and surface facilities, etc., can be optimally designed. Wells occupy a minute percentage of the total area of the reservoir and this do not give us any clue about the reservoir properties at all. Hence, the available reservoir models cannot be directly used. To overcome this difficulty, petroleum engineers usually define an inverse problem, where one quests for a few parameters that can be fed as inputs to the reservoir simulator and will yield the same production history as actually recorded in the field. The input parameters with uncertainties are several, namely, rock properties – porosity, permeability and thickness; rock fluid interaction properties – saturations, relative permeabilities, depth of oil/water and oil/gas interfaces; laboratory measured data – fluid PVT behavior, compressibility, capillary pressure data, viscosities and formation volume factors; water influx if aquifers, etc. Out of these, the most sensitive and most uncertain parameters are the porosity and permeability. Moreover, it is neither desirable nor necessary to include all other variables in optimization. Barring porosity and permeability, the rest can be tweaked manually. This is a very tedious exercise and the solution will never be unique since a large number of distributions can be found which will result in similar production histories. This process is called history-matching and was traditionally carried out manually and is a very sluggish process.

Although some reservoir engineers still use manual history-matching, more often, optimization-based automated history-matching has gained in popularity. All history-matching techniques proposed in the literature are based on the inverse modelling problem [5]. Although the main aim of history-matching is minimization of the square of data mismatch, the methods that are used for minimization as well as for evaluating uncertainty vary broadly. After manual history-matching, evolutionary algorithms were developed to automate the history-matching. The automated approach is iterative and links optimization techniques to statistical analysis and obtains the suitable best parameter combination that results in good reservoir history matching [6]. These algorithms are population-based optimization algorithms, mimicking processes happening in biological evolution. The optimization algorithm for minimizing the objective function for history-matching can be broadly divided into two categories, *viz.*, gradient and non-gradient methods.

2.1 GRADIENT BASED METHODS

These methods make use of the conventional optimization approach which has been taken up from optimal control theory to calculate solutions which will be closer to the local optimum [7]. These methods will initially calculate the gradients of the objective functions, and then, find in which direction the optimization search should go on, in order to solve the problem [8]. In the framework of the history-matching algorithm, the gradients of the production responses with respect to changes in reservoir parameters are forwarded to evaluate the magnitude and direction of the changes to be made to the parameters [9]. Various optimization algorithms that are reported ([10], [11]) in the literature are the steepest descent method, gradual deformation approach, the Levenberg-Marquardt method, the Gauss-Newton method, the singular value decomposition method, the Limited-Memory Broyden, Conjugate Gradient technique, the Fletcher-Goldfarb-Shanno and the Quasi-Newton methods.

These gradient methods require the first derivative (Jacobian) of the objective function or the second derivative (Jacobian and Hessian) of the static properties of the reservoir. They also demand an estimate of the sensitivity coefficient, which is the partial derivative of certain dynamic parameters like pressure and saturation with respect to static ones like permeability, azimuth of geospatial variogram and porosity [12]. The normal attainment is through the finite difference approximation for the partial derivative.

Kruger introduced the automation of history matching where he proposed the procedure for determining a real permeability distribution of 2-dimensional reservoir in cycling or flooding projects. He then compared the results obtained where he calculated pressure distributions with the field measurements and concluded the reservoir model to be trained for production data for trustworthy prediction of reservoir performance [13]. Two researchers, Jacquard and Jains (1965), proposed a technique of evaluating sensitivity coefficients to solve history matching problems. Here, the modified steepest descent method was used for lowering the deviation between the simulated and measured pressure arrived at with certain changes in a few parameters for a 2-dimensional transient flow, single-phase reservoir model. The reservoir model was described analogous with electrical parameters like resistance, inductance and capacitance to permeability, production rates and porosity of the reservoir model, respectively. The authors reported a successful implementation of the history-matching problem though restricted to the zonation of permeability [14].

Jacquard and Jain’s (1965) description of a nonlinear regression approach was used by Jahns to match the reservoir pressure that was obtained by interference test. The properties like transmissibility and storage term of each reservoir zone are varied with the help of regression analysis. This method was non-suitable for multiphase flow with change in fluid saturation but with single phase flow, it could easily be applicable [15]. Coats *et al.* introduced a method that is a union of linear programming and least squares, which could help assessing a linear relationship of error with the reservoir properties. The methodology of zonation was used as a method of parameterization with lower and upper boundary constraints on reservoir parameters like permeability and porosity. The reservoir description was developed with random generation of a number of runs with the help of the reservoir simulator and within the given constraints. It was used on three 2-dimensional reservoirs (one reservoir with single phase gas, another reservoir with single phase oil and the third with two phase flows) [16]. Although the method provided satisfactory matching, the validity of assumptions remained doubtful, thus limiting the application of these methodologies.

Slater and Durrer (1971) applied linear programming and a gradient-based method as a search technique to attain a finest history-matched model [17]. The modification of the gradient method of Jacquard and Jain helped find the step size and search direction for modifying the sensitivity coefficient that minimizes the objective function. It was reported that finding the step size by gradient methods in less porous and permeable regions was difficult because of the strong non-linear relationship of the objective function with lower values of the permeability and their highly sensitive nature. Thomas *et al.* (1972) applied a classical Gauss-Newton method that automatically varies the reservoir parameters that fetches a better history matched reservoir model. The method used implementation of Box-type constraints on reservoir parameters. The authors reported that their method not only gave equivalent history match on fewer simulation runs in comparison with the work of previous researchers, but also can handle non-linear cases better [3].

Carter *et al.* (1974) and Hirasaki (1975) proposed a sensitivity coefficient-based method based on the calculation of gradients. In this method, the derivatives of pressure as well as saturation with respect to sensitive coefficients (model parameters) are calculated ([18], [19]). These are later used in calculating the

Hessian matrix for second order, gradient-based optimization algorithms [20]. Carter *et al.* (1974) proposed two new iterations-based non-linear programming methods, applicable to minimize the objective function of a compressible, single phase flow reservoir. For calculating sensitivity coefficients, these techniques, however, utilized the method of Jacquard and Jain. The authors claimed that the method proved to be equally efficient to produce a good match of calculated and observed pressures when compared with earlier studies, for pre-defined constraint intervals. However, the method is limited to cases with single phase flow and needs higher computational times for calculating sensitivity coefficients with lower efficiency near the optimum solution. Hiraski (1975) proposed a semi-automatic procedure of history matching that matches oil production data only, but, was not suitable to complex reservoirs. This method was used to calculate the reservoir parameters by deducing a relation between the dimensionless cumulative injection and the derivative of cumulative oil production with respect to reservoir parameters.

Chen *et al.* (1974) and Chavent *et al.* (1975) showcased history matching problems as control problems, in which the observed data like pressure is considered as a state variable and reservoir parameters like permeability as forcing variables ([21], [22]). The adjoint method was applied to calculate the gradient of the objective function, which initially computes the derivative of the objective function and later uses a first order gradient-based optimization algorithm. It is demonstrated on a synthetic and a real Saudi Arabian reservoir (both being single phase) considering the reservoir parameters as continuous functions of space and showed that the time of computation for optimization was lower than that taken by conventional constant-zone gradient optimization method [21]. The technique was applied to a semi-realistic single phase reservoir model by Chavent *et al.* The steepest descent method and adjoint method were used to minimize a non-quadratic objective function and compute the gradients respectively, during which the generation of impractical values of transmissivities was avoided during computation. However, this methodology needs more iterations for non-linear problems and hence is more suitable for linear problems [22]. Watson *et al.* (1980) applied both the earlier methods and used the optimal control approach to successfully estimate porosity, spatially varying permeability and relative permeabilities [23].

Yang and Watson (1988) applied the variable-metric method coupled with optimal control theory, another optimization technique, for automated history matching [24]. These researchers, after testing their methodology on two 2-phase, 1-dimensional and 2-dimensional synthetic reservoir models, reported that variable-metric methods, *viz.*, self-scaling variable metric (SSVM) method and the Broyden/Fletcher/Goldfarb/Shanno (BFGS) method were more appealing in comparison with the steepest descent method and other conjugate-gradient methods, except for those cases where the performance metrics are quadratic in nature. They, hence, concluded that their method was effective in both ways, *viz.*, handling the inequality constraints and bettering the convergence rate.

Gavalas *et al.* (1976) and Shah *et al.* (1978) introduced the Bayesian framework for history matching which delivers better guesses of true porosity and permeability distributions in reservoirs as compared to the routine zone-gradient optimization methods. This probabilistic approach requires prior statistical information (*viz.*, co-variance and mean) on unknown parameters and then integrates it with the geographical information in the objective function so as to minimize the statistical uncertainty in estimating reservoir parameters ([25], [26]). The results of this study are compared with those results obtained from the sensitivity coefficient method and re-parameterization by zonation by Shah *et al.* (1978) Both the research groups, however, testified that the accuracy of the estimates noticeably depend on the accurate prior statistical and geological information.

de Marsily *et al.* (1984) proposed a method which combined the pilot point method and optimal control theory and the technique was applied to parameterize groundwater hydrology [27]. The concept was first applied to the field of petroleum engineering by Fasanino *et al.* (1986) in which reservoir parameters like the values of the permeability and porosity at predetermined pilot points were disturbed for history-matching of a single-phase gas reservoir [28]. The parameters, at locations other than the predetermined pilot points, were found out by interpolation using conditional simulation or kriging by using the parameter values at pilot points. Hence, the technique does calculate the gradient at pilot points and avoids these at all the other grid blocks, thereby reducing the unknown parameters that one has to estimate. This method offers rough solutions for the inverse problem of history matching coupled with an uncertainty about the location and the quantity of pilot points to be specified. A further extension of work on the pilot point method and its application to history matching can be seen in other studies ([29] - [33]). The pilot point method was successfully applied for estimation of values of the porosity, which, later helped in history-matching, as done by Bissell *et al.* (1997) on a synthetic reservoir [31]. Using sensitivity information figured out by a direct method which assumed that the high sensitivity regions are prejudiced by location of pilot points, optimum locations of the pilot points were established. The query of choosing the number and optimal locations of the pilot points was discussed by Cuypers *et al.* [34]. Xue *et al.* (1997) and Liu and Oliver (2004) reported certain drawbacks of the pilot point technique like slower convergence, undershooting or overshooting of reservoir parameters at the pilot points that result in massive variations of objective functions as iterations advance ([32], [35]).

The technique suggested by Carter *et al.* (1974) and Chavent *et al.* (1975) was extended further to multiphase flow studies by Anterion *et al.* (1989). The method was tested on a synthetic, fully implicit, 3-phase, 3-dimensional reservoir and reported an enhanced precision of history matched models with fewer simulation runs and lower computing time [36]. For calculating the sensitivity matrix, applications of gradient simulators are extensively studied by a few researchers ([37] - [42]). Nevertheless, their expertise suggested avoiding using direct methods, as reservoir models with a large number of grid blocks are too complex to be solved and consume higher computation time and larger memory size. Killough *et al.* (1995) introduced multiple right hand side iterative linear equation solvers (MRHS) for adjoint equations system, which enhanced the gradient solver performance. Their methodology was tested on reservoir models up to 10,000 grid blocks and the results obtained from the MRHS iterative solver were compared with those obtained from the standard red-black line successive over-relaxation and direct solvers [43].

A modified Gauss-Newton method was utilized to solve history-matching problem of a 3-dimensional synthetic reservoir for estimating the porosity and permeability by Tan and Kalogerakis (1992). The authors executed the methodology successfully to completely automate the procedure of history matching that helped in attaining genuine values of porosity and permeability. They have also reported that the Gauss-Newton method is capable of decreasing the number of sensitive coefficients to be evaluated [44]. Chu *et al.* (1995) employed this technique for history matching of a single-phase reservoir and attempted to condition the well-test pressure information with the porosity and permeability distributions of the reservoir grid block, with the modified generalized pulse-spectrum technique. These researchers reported that the technique accomplished a reasonable evaluation of the permeability distribution but not the porosity distribution [45]. Reynolds *et al.* (1996) used this Gauss-Newton methodology for multi-well pressure data history matching to assess reservoir parameters, where a subspace method was applied, to reduce the size of the Hessian matrix, as parametrization technique. The authors declared that notable reduction is seen in the computation time taken for producing realizations [46]. Methodology of Chu *et al.* (1995) was applied by He *et al.* (1997) for 1-phase flow reservoir & generated porosity fields' sensitivity coefficients [47]. The method was further applied by Li *et al.* (2003) to a 3-D, three phase reservoir problem. Researchers suggested that Gauss-Newton method as well as its variants gave highly mismatched well-test pressure data when the process started with bad initial guesses. They also reported leisurely convergence for large volumes of production data [48].

The Levenberg-Marquardt method, a variant of the Gauss-Newton method, was used by Bi *et al.* (2000), where the Hessian matrix was modified for a better convergence rate. These researchers have employed the technique to condition 3-

dimensional stochastic channels to well observations and well-test pressure data [49]. Zhang *et al.* (2003) presented a randomized maximum likelihood (RML) method that gave a good initial population for the algorithm and used the Levenberg-Marquardt method to condition 2-dimensional stochastic channels to well observations and pressure data [50]. This method was later used by Vefring *et al.* (2006) for estimation of properties of reservoirs by minimizing the variance between the reservoir simulation model states and corresponding measurements from the drilling process. The algorithm showed a slower convergence rate and also brought instability for reservoir models with large number of parameters and huge production data [51].

The higher efficiency of the conjugate gradient or quasi-Newton method can be attributed to the fact that this method needs gradients of the objective function to be calculated, thus reducing the computational time. Makhlouf *et al.* (1993) used this approach for estimating values of the permeabilities of grid blocks of a reservoir with 2-phase and 3-phase flows [52]. For complex history-matching problems, limited memory BFGS (LBFGS), another variant of the quasi-Newton method, was employed. This proposed method uses values of the objective function and gradient, from the preceding iteration that constructs the Hessian approximation. These researchers reported extensively on several gradient optimizers, *viz.*, pre-conditioned conjugate gradient, LBFGS, BFGS and Levenberg-Marquardt for real and synthetic reservoirs and concluded that the LBGFS is relatively more efficient than the rest [12]. Liu and Oliver (2004) tested the use of the adjoint equation for calculation of the gradient and the quasi-Newton method as minimizing algorithms on a 5-spot water injection problem that has around 70,000 model parameters [35]. Eydinov *et al.* (2009) described the application of the LBFGS algorithm for evaluating the relative permeability curves and porosity and permeability distribution for a 3-phase synthetic reservoir [53].

Parish *et al.* (1993) formulated a knowledge-based system (KBS) for reservoir engineers that acts as a decision support tool. The KBS uses instructions like IF

THEN, ELSE, statements to make appropriate history matching decisions [54]. Roggero and Hu (1998) proposed a stochastic optimization method called as the Gradual Deformation method as a substitute to the conventional gradient optimization method for conditioning a stochastic 3-dimensional reservoir model to the production and well-test data. The problem is formulated as a linear combination of two Gaussian realizations with expected covariance and mean to create new realizations that match better than the initial generations. The matches are further enhanced by integrating them with other equi-probable realizations. The process was not stopped until a tolerable match is obtained [55]. Later, Hu (2000) made an extension to this methodology and studied various deformations including multi-dimensional gradual deformations as well as locally gradual deformation corresponding the structural parameters [56].

It was further extended and Hu *et al.* (2001) affirmed its efficacy obtained by simulator that can constrain facies models of reservoir [57]. After realizing that by using gradual deformation algorithm they have not achieved better samples of posterior probability density function, an extra constraint was appended in the fitness function which had mismatch in data earlier by Ravalec-Dupin and Noetinger (2002) [58]. Caers (2003) applied the gradual deformation method with multi-point geostatistics for a streamline simulation model to generate initial realizations for history matching [59]. A conclusion was drawn by Liu and Oliver (2004) that the gradual deformation method achieved much better results than those obtained by the Markov Chain Monte Carlo method [35].

The above discussed types of gradient-based techniques quickly converge to the optimal solution but does not guarantee global optimum solution. Also, they involve calculating first and higher order derivatives of highly nonlinear objective functions. Hence, researchers had to divert their focus onto non-gradient based stochastic methods to overcome these drawbacks.

2.2 NON-GRADIENT BASED METHODS

Non-Gradient based methods (stochastic algorithms) have certain advantages over gradient based methods. These methods are helpful in approaching global optima rather than being restricted to local optima compared to gradient methods and do not involve rigorous calculations for minimizing the objective function. They involve large computation time and large numbers of simulation runs, so that the solution converges to a global optimum. These do not require initial guesses in the vicinity of the optimum solution, which make them applicable for non-unique history matching. In non-gradient based methods, with the help of certain operators, a number of equi-probable reservoir models evolve progressively, until the global optimum is reached. Various algorithms based on non-gradient based methods are now in use, *viz.*, Simulated Annealing (SA), Scatter Search (SS), Neighborhood Algorithm (NA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Kalman filters (KF) and Genetic Algorithms (GA).

2.2.1 Simulated Annealing (SA)

Simulated annealing (SA) is a probabilistic technique that approximates the global optimum of a given function. This was introduced by Kirkpatrick *et al.* (1983) and Cerny (1985) ([60], [61]). In a large search space, it is a metaheuristic to approximate global optimization and is used often for cases with more discrete search spaces. The methodology has been applied for estimating of petrophysical properties of a reservoir and conditioning concurrently [62]. These researchers used the technique for estimating the capillary pressure for gas/water and relative permeability curves simultaneously.

Sultan *et al.* (1993) applied SA on a black oil reservoir which was experiencing water flooding for automatic history matching and reported that the values predicted are in good match with the observed field production data [63]. Ouenes and Saad (1993) suggested a novel SA algorithm that helps in reducing computation time and applicable for large scale reservoirs for minimizing the objective function [64]. Ouenes *et al.* (1994) applied SA for a fractured reservoir and estimated the reservoir wettability, pore volume, permeability and wellbore properties [65]. Sagar *et al.* (1995) applied the SA technique and minimized an objective function that comprised of average permeability data besides the spatial statistics of the reservoir obtained from well log/core data [66]. A heat-bath algorithm was proposed for SA by Sen *et al.* (1995) and was applied for predicting permeability fields [67]. Abdassah *et al.* (1996) integrated acoustic impedance data with the conventional SA method and achieved a better reservoir simulation [68]. Portellaand and Frais, (1999), used the technique of SA integrated with the pilot point method to solve automatic history matching problem [69].

2.2.2 Scatter Search (SS)

The technique of Scatter Search is unique, in that it stores given information about the global optima in a diverse and elite set of solutions and later exploits this to recombine samples. It is an iterative process, in which the initial population is partitioned into subsets and the subsets are combined linearly with certain weights. The outcomes of recombination are fine-tuned with the help of an embedded heuristic and are evaluated for the condition whether or not they should be retained. Sousa *et al.* (2006) applied the SS technique and history matched heterogeneous and homogeneous synthetic reservoirs. The problem was framed as an optimization problem with uncertainties in parameters to be discretized. This resulted in enhancing the accuracy of the outcomes which increased the possible solutions in number [70].

2.2.3 Neighborhood Algorithm (NA)

It is a global optimization, non-derivative search algorithm in a Bayesian framework which is used for sampling the multi-dimensional parameter space. Random model sets are generated initially and are then ranked according to the data match. Geometrically constructed spatial properties, called as Voronoi cells, are utilized to build up new models from the previous best matched models.

The NA algorithm is used to develop history matched models. NA was introduced to reservoir applications for highly non-linear problems such as seismic data waveform inversion by Sambridge (1999). He claimed that the technique was consistent with the distributed systems [71]. Later, a few other researchers, Subbey *et al.* (2004) and Christie *et al.* (2006), used a Bayesian framework for quantifying uncertain parameters in flows through porous media and developed history matched models applying NA ([72], [73]). Rotondi *et al.* (2006) used the technique of NA for an offshore gas field that has 7 wells and for which 6 years production data was available. They reported that the uncertainty quantification done using Bayesian inference and forecasts of production of hydrocarbons matched accurately with data, in comparison to other history matching algorithms [74]. The Erbaş and Christie (2007) study was more focused on determining the inaccuracies that are associated with various sampling algorithms for quantification of uncertainties in parameter estimation and reservoir performance predictions. They scrutinized the efficiency of NA for generating history-matched models of a real field from the North Sea reservoir [75]. Suzuki *et al.* (2008) pooled NA with 'similarity distance' measure in order to make it applicable for large reservoir realizations [76].

2.2.4 Particle Swarm Optimization (PSO)

PSO is a population based stochastic optimization technique, which is developed by Kennedy and Eberhart in 1995. It is a bio-inspired technique and is used for continuous and discrete optimization problems. In PSO, the possible solution sets are called 'particles' which are mobile throughout the search space and the site of a particle represents a solution for the problem [77].

Kathrada (2009) has applied PSO on a synthetic reservoir, when he evaluated the technique in conjunction with hierarchal clustering algorithm and generated history matched models [78]. PSO was applied by Fernandez Martinez *et al.* (2009) for seismic history matching where the subsurface facies model is conditioned to match seismic data with time-lapse and production history. These researchers claimed that the methodology is equally good in comparison to other optimization techniques when it comes to convergence as well as uncertainty quantification [79]. Ali Ahmadi *et al.* (2013) have joined PSO with soft sensor based on ANN based soft-sensor and GA and tested its application to real field [80]. Literature suggests that the PSO can also help in finding out the optimum locations of wells ([81] - [83]). Awotunde (2012) upgraded the basic PSO technique and developed multiple history-matched models of permeability distributions [84].

2.2.5 Ant-Colony Optimization (ACO)

ACO, an evolutionary approach and applicable to continuous as well as discrete variable optimization problems, was introduced by Dorigo *et al.* (1996). It is a population based stochastic optimization method which exploits the swarm intelligence and is evolved from the social behavior of ants [85]. As proposed by Razavi and Jalali-Farahani (2008), the ACO technique can be used to predict well flow pressure, fluid injection rates and optimal well locations for injection and production [86]. Rutkowski *et al.* (2008) applied a multidimensional, continuous ACO for evaluating the optimum number of phase separators required in an oil industry [87]. Oil-bearing zones of a reservoir are also recognized by applying a hybrid particle swarm-ACO algorithm (PS-ACO) [88].

Hajizadeh (2011) and Hajizadeh *et al.* (2011) extensively studied differential evolution (DE) algorithm and ACO on two reservoirs and achieved a few history-matched reservoir models. These researchers claimed that ACO provided better-quality multiple history-matched models and took fewer simulation runs in comparison to the DE algorithm ([89], [90]).

The ACO combined with the back-propagation algorithm, was proposed by Irani and Nasimi (2012) and Hatampour *et al.* (2013). They tested the algorithm for predicting permeability distributions from well log data and proved that the algorithm was more effective than the conventional BP algorithm. ACO was applied for analyzing waterflood for an oil reservoir with high porosity, low permeability and high oil saturation ([91], [92]).

2.2.6 Ensemble Kalman Filters (EnKF)

The EnKF has originated as another version of the Kalman filter for complex problems where the sample covariance replaces the covariance matrix [93]. It is a recursive filter, wherein, when new data arrives, it computes the next step instead of running the full optimization over the horizon, which makes it suitable for problems with huge number of variables. EnKF is utilized to update not only static parameters, but also dynamic variables of the reservoir model. The EnKF calculations generally rely on the reservoir model's ensemble of realizations. The model predictions are combined with new measurements, when available, and the realizations get updated.

Naevdal *et al.* (2002) applied the EnKF for updating static parameters by fine-tuning the permeability fields [94]. Gu and Oliver (2005) used EnKF and continuously updated permeability, porosity, saturation fields and pressure of a 3-dimensional reservoir history matching problem. They claimed a fairly good history match with reduced computational cost by using small ensemble size. However, issues related to porosity and permeability fields overshooting were pointed out [95]. EnKF was used in conditioning lithofacies realizations generated by pluri-Gaussian model of Liu and Oliver (2005). They have compared the EnKF performance with that of gradient-based minimization method for estimating the facies boundaries. It was reported that EnKF was found to be more effective for history matching the production data [96]. EnKF with an option of confirming was applied by Wen and Chen (2005) to match production data. The authors testified that ensemble size of anything less than 200 will not be able to predict the model uncertainties [97].

Gao *et al.* (2006) made an attempt to compare the results of EnKF attained uncertainty quantification with the ones computed with the help of Bayesian setting with randomized maximum likelihood (RML). The authors have testified that results are comparable [98]. Skjervheim *et al.* (2007) have utilized EnKF to update the model regularly by assimilating production datum and the obtained 4-D seismic datum that has resulted in better permeability field estimate [99].

Haugen *et al.* (2008) have tested EnKF for reservoir history matching by envisaging water to oil contact & gas to oil contact. However, it was not very successful, as a few issues corresponding to structural parameters' predictions as well as facies distributions (non-Gaussian) were doubted by researchers [100]. The authors, Chen *et al.* (2009) proposed one technique with closed loop that has an optimization scheme based on new ensemble with EnKF (EnOpt) which does not need any adjoints [101]. Later, the researchers, Agbalaka and Oliver (2008) utilized the methodology of EnKF to automate history-matching of facies distribution along with production data. Satisfactory results were reported by them, wherein a sub-spaced methodology was utilized for a 1-phase flow of 2-D and 3-D reservoirs with synthetic pressure data [102].

EnKF was applied for history matching and characterization of an unconventional 3-dimenstional steam-assisted gravity drainage oil reservoir by Chitralekha *et al.* (2010). The quality of ensemble realizations was assessed in terms of R-square values and their weighted mean square error (WMSE) for distance dependent covariance globalization and localization methods that were used for updating the values of the permeabilities. It is observed that least error permeability values are obtained by the localization method. The EnKF algorithm estimated permeability distribution which are compared to those of a 3-dimensional synthetic reservoir and gave lower root mean square error (RMSE) for localized EnKF algorithm than with the global EnKF algorithm [103].

Emerick and Reynolds (2011) significantly improved history matching and performance prediction by applying the half-iteration EnKF (H-EnKF) combined with the covariance localization method. The authors reported performance comparison of a real reservoir between H-EnKF with covariance localization and without covariance localization, and claimed that the former method provided better history matching and performance prediction [104]. Another variant of the

EnKF method, the constrained EnKF (CEnKF) technique, was proposed by Phale and Oliver (2011), which also accounts for constraints on credible values of certain state variables while data assimilation. These researchers claimed that the technique attained better prediction of reservoir properties by enforcing bound constraints on saturations and non-negativity constraints on molar densities [105]. Zhang and Oliver (2011) studied the uncertainties related with geological structures and proposed a technique that updates multiple scales of heterogeneity in the Ensemble Kalman filter. These researchers reported that the results obtained have shown better history matching and water cut match [106].

In order to minimize the sampling error that is occurring at a single update step of EnKF, Kovalenko *et al.* (2012) derived the Euclidean norm distribution of the sampling error evolving at the single step update assuming normality of forecast distributions and negligible observation error. The methodology was applied on a few synthetic reservoir models and the propagation of error at single step update was illustrated [107]. A parallel data assimilation framework for quantifying uncertainty and characterization of reservoir was introduced by Tavakoli *et al.* (2013), who disbursed multiple realizations among various computers for computations. A network was built and the communication among these computers was done at the data assimilation step. The technique was tested on a synthetic reservoir for Ensemble Smoother (ES) method besides EnKF. These researchers concluded that the computation time was reduced and a parallel efficiency of 50% was attained for ES in comparison with 35% attained for EnKF [108].

Leeuwenburgh and Arts (2014) proposed an alternative distance parametrization which does not need additional simulation time. The author claimed that the proposed technique incessantly shrinks data though still retrieving the required important information that results in efficient functioning of EnKF [109]. A novel and better parametrization based on truncated Gaussian simulations was introduced by Abadpour *et al.* (2017) to ensure geological realism of history matched models. The authors applied this technique and generated realizations, consistent with geological hypothesis, that are constrained to reproduce the field measurements [110]. History matching study based on connection information using EnKF was attempted by Zha *et al.* (2018), where well water cut and connection water cut of each layer was chosen as production data. The authors reported better results with less simulation time [111].

2.2.7 Genetic Algorithm (GA)

It is a mathematical modelling algorithm which is based on Darwin's 'survival of the fittest'. It is a computer-based search procedure inspired from genetics, which has widespread application. This process utilizes an initial population of individuals, known as chromosomes, which are further processed where they undergo inheritance, crossover and mutation operations for several generations that obtains potential solutions. The new generation chromosomes are evaluated based on a fitness function.

The methodology of GA has been applied widely in innumerable engineering as well as real-world problems, *viz.*, learning robotic behavior [112], prediction of protein structure [113], inverse problems in the field of electromagnetics [114], designing an optimal neural architecture for developing online soft-sensor [115] and several more.

GA is proved to be an efficient method for inverse history-matching problems and reservoir parametrization. Sen *et al.* (1995) introduced the application of GA for reservoir modelling and generated permeability distributions from tracer flow data and a set of reservoir outcrops, followed with quantifying uncertainties in production forecasts. With a population size of 200, they could achieve global optimum solution with values of 0.60, 0.01 and 0.9 as crossover probability, mutation probability and update probability, respectively. The researchers also reported that the choice of these probabilities and population size largely affects the performance of GA [67]. A modified GA for estimating fault throw, shale permeability and sand permeability was proposed by Bush and Carter (1996) that used steady state genetic algorithm with modified rank selection operator. They claimed that this modified GA when tested on a synthetic PUNQ-S3 reservoir outclassed the standard GA [116]. Guerreiro *et al.* (1998) tested GA to determine properties of a reservoir by systematically matching tracer breakthrough profiles utilizing parameters such as porosity outside and inside the insertion and geometry of insertion. With a population size of 200 and using three different crossover operators in their studies, *viz.*, single point operator, two-point operator and uniform cross over operator with values of their probabilities as 0.08, 0.48 and 0.24 respectively and the bit-flip mutation probability as 0.02. They used a rank-based elite selection that is helpful in selecting the best realization as per the fitness value and reported that the methodology achieved satisfactory results [117].

A neural-genetic model for estimating permeability from well log data was developed by Huang *et al.* (1998) that utilized GA for optimizing connection weights used for training neural networks. They reported that, though GA consistently reduced the performance error as compared to neural networks, convergence was slower [118]. However, by integrating a fuzzy reasoning, the neural-genetic model was modified to hybrid neural-fuzzy-genetic methodology that gave faster convergence [119]. Soleng (1999) used steady state GA for fine-tuning petrophysical properties such as porosities and permeabilities, of the PUNQ S3 synthetic reservoir to actual observations. He claimed the technique was reasonably fast at achieving near-optimal solutions in the vicinity of realistic reservoir conditions, with a population size of 50. He also suggested the use of a 3-dimensional crossover operation to nullify the disturbing effect of crossover. He applied the technique successfully to a small reservoir, taking a few parameters into account for conditioning the field observations, but doubted its efficiency for a large-scale reservoir [120].

Romero and Carter studied the GA optimizer and tested extensively on the PUNQ S3 complex synthetic reservoir for history matching and its results are compared with those obtained from SA and GA with hill climbing (2001). Various parameters like V-shale, permeability and porosity were encoded in a complex 3-dimensional chromosome structure for which a bit-flip crossover operation is used. All other parameters like well-skin factors, relative permeability end points were encoded in 1-dimensional chromosome for which k-point crossover operator is used. The researchers claimed that they achieved better results with the GA optimizer than with SA and manual history matching [121].

A novel concept, top down reservoir modelling (TDRM), was proposed by Williams *et al.* (2004) for history matching of production data and quantifying uncertainties. The TDRM is currently trademarked technology of British Petroleum. This approach utilizes a GA optimizer in combination with a reservoir simulation model to determine sensible multiple history-matched models. The tool was successfully applied to 18 gas and oil reservoirs. They have reported that a 20% increase in the predicted net present value (NPV) of projects resulted through the TDRM approach [122]. The TDRM workflow was successfully applied in the British Petroleum Trinidad and Tobago assets to determine ideal well locations in an oil field with production history available for 30 years from 13 wells by Kromah *et al.* (2005) [123]. Apart from TDRM, GA is also used in MEPO® and ENABLE®, commercial software that are helpful in improving the quality of history matched models. Choudhary *et al.* (2007) attempted quantifying subsurface uncertainty, automatic history matching and infill well optimization, using MEPO® for two West African mature fields [124].

The modelling of a fractured reservoir using available field data is often difficult and levies large computational costs. Lange (2009) used discrete fracture network flow simulator (DFN) coupled with GA based inversion methodology for characterizing such reservoir models [125]. Han *et al.* (2011) proposed multi-objective optimization (MOO) utilizing an altered GA optimizer for production history matching of water-flooding projects. The methodology was tested on a 2-dimensional heterogeneous reservoir with 1 injection well and 3 production wells, divided into 400 grid blocks. These researchers reported better prediction with small performance error and a better estimate of reservoir parameters with their method [126].

Dehghan Monfared *et al.* (2012) combined subsurface response modelling with GA for inverse history matching. These researchers constructed proxy reservoir models which constitute as simulator response, with the help of available measurements. They then built a reservoir model which is based on minimized proxy model generated by GA, which took fewer runs and less time at lower cost in comparison with other techniques. The same has been tested on a field whose production history is known for 41 years and history-matched models were achieved which were fairly consistent with water cut, shut-in pressure, observed oil rate and repeated formation test pressure [127]. Murgante *et al.* (2012) tested GA and differential evolution (DE) on four case studies each with varying number of parameters, for history matching [128]. Ahmadi *et al.* (2012) designed a soft sensor to predict permeabilities of a real reservoir, based on a feed-forward neural network. The authors used PSO and a hybrid GA for optimizing the soft sensor. Values of the reservoir parameters' optimal weights were attained using GA. Also, the effectiveness of the proposed methodology was demonstrated from the results obtained from the developed soft sensor and conventional neural network [80]. The usage and application of Adaptive Genetic Algorithm (AGA) coupled with higher order neural networks (HONN) for reservoirs' history matching as well as for oil production forecasting respectively was explored by Chakra [2]. However, the author reported that the grid block size used in her studies must have introduced some error as a coarse grid block size was chosen.

Min *et al.* (2014) proposed a vigorous Pareto-based history matching model that accounts for complex relationships among well performances. The methodology, integrated with Successive Linear Objective Reduction (SLOR) and Dynamic Goal Programming (DGP) for dimension-reduction and preference-ordering respectively, named as DS-MOGA (DGP and SLOR with Multi-objective Genetic Algorithm), was applied to a heavy oil reservoir for history matching and production forecasting. These researchers have reported that multiple qualified trade-off solutions can be obtained using this methodology when compared to traditional MOO techniques [129]. While solving history matching and optimization problems, there is a possibility to come across several potentially conflicting objectives. The objective functions involving multiphase production history, differences in reservoir pressure and 4-dimensional time-lapse seismic data are a few examples that are potentially conflicting. Park *et al.* (2015) proposed a Pareto-based multi-objective evolutionary algorithm (MOEA) that directly uses the dominance relation for fitness function. They applied the proposed Pareto-based MOEA to 2-dimensional synthetic and 3-dimensional real reservoirs and reported that their methodology outperforms conventional GA that is used for history matching [130].

Kam et al. (2017) have demonstrated the utility of a multiscale approach by combining MOGA for global history-matching with a streamline-based joint inversion for local calibration. They history-matched three-phase production data and bottom hole pressure. The method was tested on the Norne field in the North Sea [131]. Carneiro et al. (2018) successfully evaluated a geostatistical multi-objective history matching method to the benchmark PUNQ-S3 reservoir problem where 12 objectives were targeted [132]. They claimed that the purpose of history matching was achieved, without suffering significant computational costs, the credit of which is due to the selection criteria used in the cascading selection step. Zhang et al. (2019) have utilized a diverse subset of history matched models to generate optimal solutions using NSGA-II for optimal design of chemically enhanced oil recovery. The authors have implemented History matching quality index (HMQI) with Moving linear regression analysis to evaluate simulation results from history matching process [133]. A hierarchical multi-scale history matching methodology was presented which has attempted to combine GA with streamline method for calibration of fracture permeabilities for a HPHT tight gas reservoir located in China using dual porosity models by Chen et al.(2020) [134]. Chai et al. (2021) proposed a hybrid approach of GA and PSO optimization techniques, named as Genetical Swarm Optimization (GSO) and developed optimal field development strategy for a South Cowden reservoir in which water flooding has been implemented [135]. A history matched model developed using the application of NSGA-II combined with multi-resolution reduced physics model was used for performance prediction and drainage volume visualization by Fu et al. (2023) [136].

In this research, two techniques viz. NSGA-II and NSGA-II coupled with Sequential Gaussian Simulation (SGSIM) are applied to the problem of history matching. Novelty of the work is application of NSGA-II and coupling NSGA-II with SGSIM, for the problem of history matching. In order to reduce the large number of variables, a network of pilot points is chosen and a geo-statistical interpolation approach (SGSIM) is used to estimate the other variables.

CHAPTER 3

SIMULATION APPROACH TO FLUID FLOW THROUGH A POROUS MEDIUM

Reservoir modeling has two major components: static model and dynamic model. Static model, specifically provides the framework of geological and structural features of the reservoir found during the exploration stage. The geologist does the job of mapping the sedimentary rock layer outcrops for locating the subsurface structural traps like domes and anticlines. Petroleum geologists identify the subsurface structure by applying geological techniques such as 2D, 3D seismic surveys, satellite images, sparse well log data and borehole images. Wireline well logs and seismic surveys are helpful in recognizing the stratigraphy of the reservoir and trace the relation between the rock layers. The reservoir boundary, zonation and sectoring are included in the geological modeling. Seismic interpretations play a vital role in identifying the rock deformations such as faults or folding and tilting. Porosity and permeability and their distributions at locations other than sampling locations, evaluated using geostatistical method, are also defined in the geological model. However, the reservoir model becomes dynamic when the rock-fluid properties such as connate water saturations, fluid saturations, relative permeabilities and aquifer properties are incorporated in the reservoir to understand the fluid movement within the system. After the reservoir model is equipped with all such details (some of them such as rock static properties may be tentative), one can proceed to evaluate the movement of the reservoir fluids (oil, gas and water) under the available driving force. This is called flow simulation.

Reservoir flow simulation is a crucial task to predict the performance of the reservoir under study. The reservoir simulator mainly comprises of a set of non-linear partial differential equations that have suitable initial and boundary conditions, which can describe the hydrodynamic fluid flow behavior within the reservoir over time. In this chapter, the formulation used for black oil reservoir modeling model is described. Black oil modelling is used for reservoir situations where fluid flow behavior is modeled using reservoir pressure and not considering the effects of fluid phase composition on flow behavior. Black oil model assumes oil and gas to be single components and no mass transfer is allowed between phases. This is strictly not true but is a reasonable approximation for heavy oil. These models have been successfully applied to water flooding, inert gas injection, etc. However, these models do account for the solubility of gas in oil and water, dependent only on pressure. In the black oil flow model, the fluid properties characterized by the PVT table that comprise of formation volume factors and solution gas-oil ratios vary as a function of pressure. Compositional models, on the other hand, consider oil and gas to be composed of individual hydrocarbons such as methane, ethane and heavier components. Mass transfer is allowed to take place based on vapor-liquid equilibrium (VLE). In compositional flow model, the PVT table additionally includes changes in the fluid compositions (oil and gas mole fractions) as a function of pressure. Hence, in case of compositional models, it is necessary to write material balance equations, component-wise, unlike black oil models where these equations can be written based on phases (oil, gas and water). The formulation of partial differential equations for reservoir modeling presented in this chapter is adapted from the literature ([137]).

3.1 DEFINITION OF PROPERTIES

There are various rock and fluid properties in the context of petroleum reservoirs, which are used in developing a numerical model. Definitions of these properties are given below.

Porosity (φ): Rock porosity represents the void space in the porous media, where the fluids get accumulated. Porosity is defined as the ratio of pore volume to the total bulk volume of the rock. It is expressed either in fraction or percentage and is a dimensionless quantity. The porosity of rock can be mathematically expressed as:

$$\varphi = \frac{Pore\ volume}{Total\ volume} \tag{3.1}$$

If the rock is compressible, porosity is dependent on the fluid pressure. There are, mainly, two types of porosity, effective and total porosity. The effective porosity is the ratio of interconnected pore volume to the bulk volume, whereas, the total porosity represents the ratio of total volume of the pore space to the bulk volume.

Permeability (*k*): It is termed as the capability of a rock to transmit fluid through the interconnected pore space. Mathematically, it is defined by Darcy's law which states

$$q_x = -\frac{k\ \Delta P\ A}{\mu L} \tag{3.2}$$

where, q_x is the flow rate in the *x*-direction, $\Delta P/L$ is the pressure gradient causing the flow, *A* is the flow area and μ is the fluid viscosity. It is expressed in Darcy or millidarcy (mD). When the reservoir rock is completely saturated with one phase fluid, it is termed as absolute permeability. Effective permeability is the capability of the rock to transmit fluid through interconnected pore space, in presence of other immiscible fluids. Permeability is also a rock property and therefore, varies with space and flow directions.

Fluid Saturation (*S*): Saturation can be termed as that percent, or fraction, of the pore volume occupied by a particular fluid phase (oil, gas, or water) in the void space. Saturation is mathematically defined as:

$$S = \frac{Total\ Volume\ of\ the\ Fluid}{Pore\ Volume} \tag{3.3}$$

All saturation values are based on pore volume and not on the gross reservoir volume. The saturation of each individual phase ranges between 0 to 100%. For a three phase fluid flow of oil, gas and water, the sum of the saturations is 100%, i.e.,

$$S_o + S_g + S_w = 1 \tag{3.4}$$

where, S_o, S_g and S_w corresponds to the fractional saturation of oil, gas and water, respectively.

Capillary Pressure (P_C): When two immiscible fluids are in contact, there is a discontinuity in pressure between them, which primarily depends on the curvature of the interface separating these fluids. This difference in pressure is referred to as the capillary pressure and mathematically defined as

$$P_C = P_{nw} - P_w \tag{3.5}$$

where, P_w and P_{nw} are the pressures in wetting and non-wetting phases respectively. That is, the pressure excess in the non-wetting fluid is the capillary pressure, and is a function of saturation.

Relative Permeability (k_r): When there is a simultaneous flow of two or more fluids, at a specific saturation, the ratio of the effective permeability of the corresponding phase to the absolute permeability is termed as the relative permeability of the corresponding phase. It is affected by the pore geometry, wettability, fluid viscosity and saturation history. The relative permeability is dimensionless and varies between zero and one.

$$k_r = \frac{Effective\ permeability}{Absolute\ permeability} \tag{3.6}$$

When the reservoir displacement process is dominated by gravity, the relative permeabilities are functions of saturations, and it is only essential to know the end-point saturations, the irreducible water saturations and the residual oil saturations. The residual oil saturation is an important parameter used to determine the overall oil recovery.

Mobility (λ): The ratio of the effective permeability to the phase viscosity is termed as mobility of a fluid phase. It is expressed as

$$\lambda = \frac{Effective\ permeability}{Phase\ viscosity} \qquad (3.7)$$

Phase: Phase is a homogeneous region of a fluid separated from another phase by an interface, e.g., oil, gas or water. Two phases are said to be immiscible if both the phases cannot be mixed in any proportion to form a homogeneous solution.

Component: Component refers to a single chemical entity that may be present in a phase, e.g., the aqueous phase contains components like water (H_2O), sodium chloride (NaCl) and dissolved oxygen (O_2).

Compressibility (C_f): The change in volume (*V*) or density (ρ) of the fluid with respect to the pressure (*p*) is termed as the compressibility of the fluid and is expressed as

$$C_f = -\frac{1}{V}\left(\frac{\partial V}{\partial p}\right)_T = -\frac{1}{\rho}\left(\frac{\partial \rho}{\partial p}\right)_T \qquad (3.8)$$

3.2 DEVELOPMENT OF FLOW EQUATIONS THROUGH POROUS MEDIUM

The flow equation for a black oil model can be derived in a stepwise manner from the conservation of mass equation and Darcy's law, utilizing fluid potentials and constraints on saturations.

The equation for the conservation of mass can be generally written as

Mass in - Mass out + Mass generated - Mass depleted = Mass accumulated

Initially, the multiphase flow equations can be formulated for 1-D flow, which can be expanded further for 2-D and 3-D flows. Consider an element (Fig 3.1) of reservoir of dimensions, Δ*x*, Δ*y* and Δ*z*.

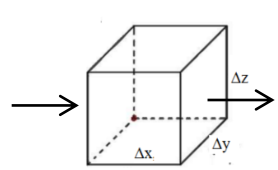


Figure 3.1: Element of a reservoir with dimensions Δ*x*, Δ*y* and Δ*z*

For 1-D fluid flow in the x-direction, applying the conservation of mass equation leads to

$$\{[\dot{m}_{cx}A_x]_x - [\dot{m}_{cx}A_x]_{x+\Delta x}\}\Delta t + q_{mc}\Delta t V_b = V_b[(m_{vc})_{t+\Delta t} - (m_{vc})_t] \quad (3.9)$$

where, $\dot{m}_{cx}$ = mass flux of component 'c' (c = oil, gas or water)

A_x = cross-sectional area of flow in the x direction (= $\Delta y\Delta z$), independent of x

Δt = time interval

q_{mc} = mass flow rate of component 'c' per unit volume

q_c = volume rate of component 'c' per unit volume

V_b = volume of the element = $\Delta x\Delta y\Delta z = A_x\Delta x$

m_{vc} = mass of component 'c' per unit volume of porous medium.

Eqn (3.9) gives

$$-\frac{\partial(\dot{m}_{cx})}{\partial x} + q_{mc} = \frac{\partial(m_{vc})}{\partial t} \quad (3.10)$$

For any phase, 'i', the mass flux is the density times the Darcy velocity:

For oil, $\dot{m}_o = \rho_o u_o$ (3.11a)

For water, $\dot{m}_w = \rho_w u_w$ (3.11b)

For free gas, $\dot{m}_{fg} = \rho_g u_{fg}$ (3.11c)

For the solution-gas,

$$\dot{m}_{sg} = (\rho_{gsc}\frac{R_s}{B_o})u_o \quad (3.11d)$$

Here, B_i is the formation volume factor of phase, 'i', defined as the ratio of volumes of the reservoir pore space of 'i', to the volume of 'i' at standard conditions, i.e., $B_i = \frac{\rho_{isc}}{\rho_i} = \frac{q_i}{q_{isc}}$, with i = oil, water, gas; ρ_c = density of component 'c'; ρ_{csc} = density of component 'c' at standard conditions and R_s (= R_{so}) is the solubility of the gas in oil.

The solubility of gas in water (R_{sw}) is assumed to be negligible.

The mass of component, 'c', per unit volume of the porous medium, is given by

For c = solution gas,

$$m_{vc} = \varphi(\rho_{gsc}\frac{R_s}{B_o})S_o \tag{3.12a}$$

For c = oil, water, free gas

$$m_{vc} = \varphi\rho_c S_c, \tag{3.12b}$$

with φ = porosity and S_i = saturation of phase 'i'

Substituting (3.12b) in equation (3.10),

For oil, $-\frac{\partial(\rho_o u_{ox})}{\partial x} + q_{mo} = \frac{\partial(\varphi\rho_o S_o)}{\partial t}$ (3.13)

Putting $\rho_o = \frac{\rho_{osc}}{B_o}$ in the above, we get

$$-\frac{\partial\left(\frac{\rho_{osc}}{B_o}u_{ox}\right)}{\partial x} + q_{mo} = \frac{\partial(\varphi\frac{\rho_{osc}}{B_o}S_o)}{\partial t}$$

$$\Rightarrow -\frac{\partial\left(\frac{1}{B_o}u_{ox}\right)}{\partial x} + \frac{q_{mo}}{\rho_{osc}} = \frac{\partial(\varphi\frac{S_o}{B_o})}{\partial t}$$

$$\Rightarrow -\frac{\partial\left(\frac{1}{B_o}u_{ox}\right)}{\partial x} + q_{osc} = \frac{\partial(\varphi\frac{S_o}{B_o})}{\partial t} \tag{3.14a}$$

with q_{osc} = volumetric flow rate of oil at standard conditions per unit volume.

Similarly for water,

$$-\frac{\partial\left(\frac{1}{B_W}u_{wx}\right)}{\partial x} + q_{wsc} = \frac{\partial(\varphi\frac{S_W}{B_W})}{\partial t} \tag{3.14b}$$

For gas, which is present in the reservoir as free gas and solution gas (dissolved in oil),

$$-\frac{\partial(\dot{m}_{fgx} + \dot{m}_{sgx})}{\partial x} + (q_{mfg} + q_{msg}) = \frac{\partial(m_{vfg} + m_{vsg})}{\partial t} \tag{3.14c}$$

But, $q_{mfg} = q_{fg}\,\rho_g$ and $q_{msg} = q_o(\rho_{gsc}\frac{R_s}{B_o})$

$$=> (q_{mfg} + q_{msg}) = \rho_{gsc}(\frac{q_{fg}}{B_g} + \frac{R_s}{B_o} q_o)$$

$$=> (q_{mfg} + q_{msg}) = \rho_{gsc}(q_{fgsc} + R_s q_{osc})$$

$$=> (q_{mfg} + q_{msg}) = \rho_{gsc}(q_{gsc}) \qquad (3.15)$$

Substituting Eqn. (3.15) and Eqn. set (3.11) in (3.14c), we get

$$-\frac{\partial\left(\rho_g u_{fgx} + (\rho_{gsc}\frac{R_s}{B_o})u_{ox}\right)}{\partial x} + \rho_{gsc}(q_{gsc}) = \frac{\partial(\varphi\rho_g S_g + \varphi(\rho_{gsc}\frac{R_s}{B_o})S_o)}{\partial t}$$

Dividing it with ρ_{gsc}

$$-\frac{\partial\left(\frac{1}{B_g}u_{fgx} + (\frac{R_s}{B_o})u_{ox}\right)}{\partial x} + q_{gsc} = \frac{\partial(\varphi\ \frac{S_g}{B_g} + \varphi\ (\frac{R_s}{B_o})S_o)}{\partial t} \qquad (3.16)$$

The set of equations (3.14a), (3.14b) and (3.16) are mass conservation equations for oil, water and gas respectively for a 1-D flow of multi-phase black oil model. Each of the terms in these equations have units of volume at standard conditions per time.

The fluid potential, $\emptyset_i \equiv P_i + \rho_i g h$, where P_i = pressure of phase 'i' and h = hydraulic pressure head.

Darcy's law relates the flow velocity to the pressure gradient and is expressed as

$$u_x = -\frac{k}{\mu}\frac{\partial\emptyset}{\partial x} \qquad (3.17)$$

where k is the absolute permeability in the direction of flow, μ is the fluid viscosity and $\frac{\partial\emptyset}{\partial x}$ is the pressure gradient.

Substituting Darcy's velocity in equation (3.14a), we obtain

$$\frac{\partial\left(\frac{1}{B_o}\frac{k_o}{\mu_o}\frac{\partial\emptyset_o}{\partial x}\right)}{\partial x} + q_{osc} = \frac{\partial(\varphi\frac{S_o}{B_o})}{\partial t}$$

$$=> \frac{\partial\left(\frac{k_o}{\mu_o B_o}\frac{\partial\emptyset_o}{\partial x}\right)}{\partial x} + q_{osc} = \frac{\partial(\varphi\frac{S_o}{B_o})}{\partial t} \qquad (3.18a)$$

Similarly for water,

$$\frac{\partial\left(\frac{k_w}{\mu_w B_w}\frac{\partial \emptyset_w}{\partial x}\right)}{\partial x} + q_{wsc} = \frac{\partial(\varphi \frac{S_w}{B_w})}{\partial t} \quad (3.18b)$$

and for gas,

$$\frac{\partial\left(\frac{k_g}{\mu_g B_g}\frac{\partial \emptyset_g}{\partial x} + \frac{R_s}{B_o}\frac{k_o}{\mu_o}\frac{\partial \emptyset_o}{\partial x}\right)}{\partial x} + q_{gsc} = \frac{\partial(\varphi \frac{S_g}{B_g} + \varphi\,(\frac{R_s}{B_o})S_o)}{\partial t} \quad (3.18c)$$

Expanding $\emptyset_i$ as $\emptyset_i = P_i + \rho_i g h$, the set of equations (3.18a), (3.18b) and (3.18c) can now be written, respectively, as

$$\frac{\partial\left(\frac{k_o}{\mu_o B_o}(\frac{\partial P_o}{\partial x} + \frac{\partial(\rho_o g h)}{\partial x})\right)}{\partial x} + q_{osc} = \frac{\partial(\varphi \frac{S_o}{B_o})}{\partial t} \quad (3.19a)$$

$$\frac{\partial\left(\frac{k_w}{\mu_w B_w}(\frac{\partial P_w}{\partial x} + \frac{\partial(\rho_w g h)}{\partial x})\right)}{\partial x} + q_{wsc} = \frac{\partial(\varphi \frac{S_w}{B_w})}{\partial t} \quad (3.19b)$$

$$\frac{\partial\left(\frac{k_g}{\mu_g B_g}(\frac{\partial P_g}{\partial x} + \frac{\partial(\rho_g g h)}{\partial x}) + \frac{R_s}{B_o}\frac{k_o}{\mu_o}(\frac{\partial P_o}{\partial x} + \frac{\partial(\rho_o g h)}{\partial x})\right)}{\partial x} + q_{gsc} = \frac{\partial(\varphi \frac{S_g}{B_g} + \varphi\,(\frac{R_s}{B_o})S_o)}{\partial t} \quad (3.19c)$$

The phase pressure is expressed in terms of the capillary pressure as

$P_{Cw} = P_o – P_w$ => $P_w = P_o – P_{Cw}$

$P_{Cg} = P_g – P_o$ => $P_g = P_o + P_{Cg}$

Applying the above equations, to represent equations (3.19b) and (3.19c) in terms of P_o, P_{Cw} and P_{Cg}

$$\frac{\partial\left(\frac{k_w}{\mu_w B_w}(\frac{\partial P_o}{\partial x} - \frac{\partial P_{Cw}}{\partial x} + \frac{\partial(\rho_w g h)}{\partial x})\right)}{\partial x} + q_{wsc} = \frac{\partial(\varphi \frac{S_w}{B_w})}{\partial t} \quad (3.20)$$

$$\frac{\partial\left(\frac{k_g}{\mu_g B_g}(\frac{\partial P_o}{\partial x} + \frac{\partial P_{Cg}}{\partial x} + \frac{\partial(\rho_g g h)}{\partial x}) + \frac{R_s}{B_o}\frac{k_o}{\mu_o}(\frac{\partial P_o}{\partial x} + \frac{\partial(\rho_o g h)}{\partial x})\right)}{\partial x} + q_{gsc} = \frac{\partial(\varphi \frac{S_g}{B_g} + \varphi\,(\frac{R_s}{B_o})S_o)}{\partial t} \quad (3.21)$$

The total mass balance equation for all the phases can be obtained by performing the arithmetic calculation of multiplying eqn (3.19a) with B_o, multiplying eqn (3.21) with B_g, multiplying eqn (3.20) with B_w and then adding them.

With $\lambda_c = {k_c}/{\mu_c}$, mobility of a component ‘c’ where c = oil, water and gas,

$$\frac{\partial\left(\lambda_o(\frac{\partial P_o}{\partial x}+\frac{\partial(\rho_o gh)}{\partial x})\right)}{\partial x}+q_o+\frac{\partial\left(\lambda_g(\frac{\partial P_o}{\partial x}+\frac{\partial P_{Cg}}{\partial x}+\frac{\partial(\rho_g gh)}{\partial x})+\frac{R_s}{B_o}\lambda_o B_g(\frac{\partial P_o}{\partial x}+\frac{\partial(\rho_o gh)}{\partial x})\right)}{\partial x}+q_g$$

$$+\frac{\partial\left(\lambda_w(\frac{\partial P_o}{\partial x}-\frac{\partial P_{Cw}}{\partial x}+\frac{\partial(\rho_w gh)}{\partial x})\right)}{\partial x}+q_w = \frac{\partial(\varphi S_o)}{\partial t}+\frac{\partial(\varphi S_g+\varphi B_g(\frac{R_s}{B_o})S_o)}{\partial t}+\frac{\partial(\varphi S_w)}{\partial t}$$

$$=> \frac{\partial\begin{pmatrix}(\lambda_o+\lambda_w+\lambda_g)\left(\frac{\partial P_o}{\partial x}\right)+\lambda_o\frac{\partial(\rho_o gh)}{\partial x}+\lambda_w\frac{\partial(\rho_w gh)}{\partial x}+\\ \lambda_g\frac{\partial(\rho_g gh)}{\partial x}+\left(\lambda_g\frac{\partial(P_{Cg})}{\partial x}-\lambda_w\frac{\partial(P_{Cw})}{\partial x}\right)+\frac{R_s}{B_o}\lambda_o B_g(\frac{\partial P_o}{\partial x}+\frac{\partial(\rho_o gh)}{\partial x})\end{pmatrix}}{\partial x}+q_o+q_g+q_w$$

$$=\left[\frac{\partial\left(\varphi(S_o+S_w+S_g)+\varphi B_g(\frac{R_s}{B_o})S_o\right)}{\partial t}\right]$$

With the sum of the saturations of phases, $S_o + S_w + S_g = 1$ and the total mobility $\lambda_T = \lambda_o + \lambda_w + \lambda_g$

$$\frac{\partial\begin{pmatrix}\lambda_T\left(\frac{\partial P_o}{\partial x}\right)+\lambda_o\frac{\partial(\rho_o gh)}{\partial x}+\lambda_w\frac{\partial(\rho_w gh)}{\partial x}+\lambda_g\frac{\partial(\rho_g gh)}{\partial x}+\\ \left(\lambda_g\frac{\partial(P_{Cg})}{\partial x}-\lambda_w\frac{\partial(P_{Cw})}{\partial x}\right)\end{pmatrix}}{\partial x}+q_o+q_g+q_w+$$

$$\frac{\partial\left(\frac{R_s}{B_o}\lambda_o B_g(\frac{\partial P_o}{\partial x}+\frac{\partial(\rho_o gh)}{\partial x})\right)}{\partial x} = \left[\frac{\partial(\varphi+\varphi B_g(\frac{R_s}{B_o})S_o)}{\partial t}\right] \qquad (3.22)$$

Now, $\frac{\partial\left(\frac{R_s}{B_o}\lambda_o B_g(\frac{\partial P_o}{\partial x}+\frac{\partial(\rho_o gh)}{\partial x})\right)}{\partial x} = \lambda_o\frac{\partial\left(\frac{\partial \emptyset_o}{\partial x}\frac{R_s}{B_o}B_g\right)}{\partial x}$

$$= \lambda_o\left[\frac{R_s}{B_o}B_g.\frac{\partial^2\emptyset_o}{\partial x^2}+\frac{B_g}{B_o}\frac{\partial\emptyset_o}{\partial x}\frac{\partial R_s}{\partial\emptyset_o}\frac{\partial\emptyset_o}{\partial x}+\frac{R_s}{B_o}\frac{\partial\emptyset_o}{\partial x}\frac{\partial B_g}{\partial\emptyset_o}\frac{\partial\emptyset_o}{\partial x}+\right.$$
$$\left.\frac{\partial\emptyset_o}{\partial x}R_s B_g(\frac{-1}{B_o^2})\frac{\partial B_o}{\partial\emptyset_o}\frac{\partial\emptyset_o}{\partial x}\right]$$

$$= \lambda_o\left[\frac{R_s}{B_o}B_g.\frac{\partial^2\emptyset_o}{\partial x^2}+\frac{B_g}{B_o}\frac{\partial R_s}{\partial\emptyset_o}\left(\frac{\partial\emptyset_o}{\partial x}\right)^2+\frac{R_s}{B_o}\frac{\partial B_g}{\partial\emptyset_o}\left(\frac{\partial\emptyset_o}{\partial x}\right)^2+\right.$$
$$\left.R_s B_g(\frac{-1}{B_o^2})\frac{\partial B_o}{\partial\emptyset_o}\left(\frac{\partial\emptyset_o}{\partial x}\right)^2\right]$$

$$= \lambda_o\left[\frac{R_s}{B_o}B_g.\frac{\partial^2\emptyset_o}{\partial x^2}\right]$$

(Since the variation of $\emptyset_o$ with 'x' is small, $\left(\frac{\partial\emptyset_o}{\partial x}\right)^2 \rightarrow 0$)

$$= \lambda_o \left[\frac{R_s}{B_o}\ B_g . \frac{\partial\left(\frac{\partial P_o}{\partial x}+\frac{\partial(\rho_o gh)}{\partial x}\right)}{\partial x}\right]$$

Now, the R.H.S. of Eqn. (3.22) = $\left[\frac{\partial(\varphi + \varphi B_g\ (\frac{R_s}{B_o})S_o)}{\partial t}\right] = \left[\frac{\partial\left(\varphi(1+B_g\ \frac{R_s}{B_o}S_o)\right)}{\partial t}\right]$

$$= \varphi \left[\frac{\partial\left((1+B_g\ \frac{R_s}{B_o}S_o\right)}{\partial t}\right]$$

$$= \varphi \left[\frac{R_s}{B_o}\ B_g . \frac{\partial S_o}{\partial t} + \frac{S_o}{B_o}\ B_g . \frac{\partial R_s}{\partial t} + \frac{R_s}{B_o}\ S_o . \frac{\partial B_g}{\partial t} - \frac{R_s}{{B_o}^2}\ S_o B_g . \frac{\partial B_o}{\partial t}\right]$$

$$= \varphi \left[\frac{R_s}{B_o}\ B_g . \frac{\partial S_o}{\partial P_o}\frac{\partial P_o}{\partial t} + \frac{S_o}{B_o}\ B_g . \frac{\partial R_s}{\partial P_o}\frac{\partial P_o}{\partial t} + \frac{R_s}{B_o}\ S_o . \frac{\partial B_g}{\partial P_o}\frac{\partial P_o}{\partial t} - \frac{R_s}{{B_o}^2}\ S_o B_g . \frac{\partial B_o}{\partial P_o}\frac{\partial P_o}{\partial t}\right]$$

$$= \varphi \left[\frac{R_s}{B_o}\ B_g . \frac{\partial S_o}{\partial P_o} + \frac{S_o}{B_o}\ B_g . \frac{\partial R_s}{\partial P_o} + \frac{R_s}{B_o}\ S_o . \frac{\partial B_g}{\partial P_o} - \frac{R_s}{{B_o}^2}\ S_o B_g . \frac{\partial B_o}{\partial P_o}\right] [\frac{\partial P_o}{\partial t}]$$

So, equation (3.22) becomes,

$$\frac{\partial\begin{pmatrix}\lambda_T\left(\frac{\partial P_o}{\partial x}\right) + \lambda_o\frac{\partial(\rho_o gh)}{\partial x} + \lambda_w\frac{\partial(\rho_w gh)}{\partial x} + \\ \lambda_g\frac{\partial(\rho_g gh)}{\partial x} + \left(\lambda_g\frac{\partial\left(P_{Cg}\right)}{\partial x} - \lambda_w\frac{\partial(P_{Cw})}{\partial x}\right)\end{pmatrix}}{\partial x} + \lambda_o \left[\frac{R_s}{B_o}\ B_g . \frac{\partial\left(\frac{\partial P_o}{\partial x}+\frac{\partial(\rho_o gh)}{\partial x}\right)}{\partial x}\right] + q_o + q_g + q_w = \varphi \left[\frac{R_s}{B_o}\ B_g . \frac{\partial S_o}{\partial P_o} + \frac{S_o}{B_o}\ B_g . \frac{\partial R_s}{\partial P_o} + \frac{R_s}{B_o}\ S_o . \frac{\partial B_g}{\partial P_o} - \frac{R_s}{{B_o}^2}\ S_o B_g . \frac{\partial B_o}{\partial P_o}\right] [\frac{\partial P_o}{\partial t}] \tag{3.23}$$

Equation (3.23) is the final equation for 1-D multiphase flow.

The same can be extended to 3-D multiphase flow which will be given in vector notation by the following equation:

$$q_o + q_g + q_w + \lambda_o \frac{R_s}{B_o}\ B_g(\nabla.\nabla\emptyset_o) + \nabla.[\lambda_T\nabla(\emptyset_o - \rho_o gh) + \lambda_w\nabla(\rho_w gh) + \lambda_g\nabla\left(\rho_g gh\right) + \lambda_o\nabla(\rho_o gh) + \lambda_g\nabla\left(P_{Cg}\right) - \lambda_w\nabla(P_{Cw})] = \varphi \left[\frac{R_s}{B_o}B_g . \frac{\partial S_o}{\partial P_o} + \frac{S_o}{B_o}\ B_g . \frac{\partial R_s}{\partial P_o} + \frac{R_s}{B_o}\ S_o . \frac{\partial B_g}{\partial P_o} - \frac{R_s}{{B_o}^2}\ S_o B_g . \frac{\partial B_o}{\partial P_o}\right] [\frac{\partial P_o}{\partial t}]$$

3.3 PROCEDURE TO OBTAIN SOLUTION

The governing equations that describe flow through porous medium are highly nonlinear partial differential equations (PDE) which relate the saturation and pressure changes in space and time throughout the medium. Even with the knowledge of boundary conditions (pressure and total mass flux boundary conditions) that define the boundaries of the reservoir model, solving these equations analytically is not practical and hence, numerical solutions are pursued. Any numerical simulator converts these continuous PDEs into finite difference equations; hence, for solution purposes the entire reservoir volume is separated into three dimensional grid blocks which are almost negligible in volume when compared with the total reservoir volume. Also integration on the time scale is done in small time steps. The finite difference converts the PDEs into algebraic equations, which are subsequently solved by the matrix method. The system of equations for the simultaneous multiphase flow has to be solved for fluid pressure and saturations. For this purpose, there are different schemes for finite differences to form the approximation of PDE such as Explicit, Implicit, and the Crank-Nicholson schemes. The method of calculating the new pressure value at a later time from the pressure value at the current time, is the explicit scheme. Mathematically, it can be expressed as

$$P(t + \Delta t) = F[P(t)] \tag{3.24}$$

Instead, implicit methods find solution by solving an equation involving the current value and the later value. It can be expressed mathematically as

$$G(P(t), P(t + \Delta t)) = 0 \tag{3.25}$$

Implicit formulations are unconditionally stable but it may require large computational time whereas in case of explicit method it may be unstable and are solved for small time steps. There are various other solution procedures that can solve the simulator equations of reservoir model. They are fully implicit or IMPIS (implicit pressure and implicit saturation method), IMPES (implicit pressure and explicit saturation method) and AIM (adaptive implicit method). The IMPIS method makes use of capillary pressure relations and evaluates the phase saturations implicitly. The technique is very stable and is best suited for complex reservoir problems allowing large time-step simulation studies. Though the IMPES method is capable of solving the pressure equations implicitly for the pressure distribution and saturations distributions explicitly for each point, the method may become quite unstable for larger time step simulation studies. Therefore, it is most suited for less complicated reservoir problems. The IMPES method is simpler and faster than the IMPIS method and is applied for small time step simulations. The AIM amalgamates the advantages of both IMPES and IMPIS methods, to calculate pressure distribution and saturation. In several cases, the IMPIS method solves for grid cells in the difficult regions, which are limited in number, and IMPES method solves for simpler regions. This way, the execution time required for simulation using AIM is larger than the IMPES and smaller than the IMPIS method, which almost can save computational times from 33% to 50%.

Matrix methods are used to solve the linear equations, which result from finite difference transformation. The matrix has three diagonal elements with all other elements zero. This system of equations is again solved to find out unknown pressure and saturations over the entire volume of the reservoir. The finite difference equations are formulated to solve for the dependent parameters over the gridded domain. The spatial domain (area of reservoir) is superimposed by some type of grid which splits the space into a number of grids, cells or blocks. These grids are usually block centered or lattice type at which the dependent parameters are calculated. The spatial properties such as porosity, permeability need to be defined for each grid block in the domain. The dynamic properties; relative permeability, transmissibility, water saturations PVT properties are described such that the equations can be solved numerically. Additionally, the fault locations, oil-water interface, etc., need to be specified to find appropriate solutions.

3.4 DESCRIPTION OF RESERVOIR SIMULATOR

Various commercial numerical reservoir simulators are available for the purpose of modeling flow behavior of multiple phase fluids in porous medium. The reservoir simulator used in this study is CMG® (Computer Modeling Group Limited, Calgary). The simulation model was built using the CMG Builder® module by in-putting the available rock and fluid data. CMG developed software that performs simulation of reservoirs. Its components include pre-processors viz. Launcher, Winprop, Builder, CMOST; simulators viz. IMEX, GEM, STARS; and post-processor RESULTS. Launcher helps in file management and job scheduling and Winprop aids in PVT Phase behavior characterization whereas Builder helps in creating/editing a simulation model. CMOST aids in carrying out history matching, optimization, sensitivity and uncertainty analysis. IMEX is a 3-phase 4-component black oil simulator, GEM is a 3-phase n-component EOS Compositional simulator and STARS is a 4-phase n-component Thermal simulator. RESULTS offer grid visualization, data extraction and X-Y plots. For the present study, the reservoir model is assumed to be a black oil model and hence, CMG's black oil simulator called IMEX™ is used for simulation studies. Schematic describing the simulation is as shown below in Fig. 3.2.

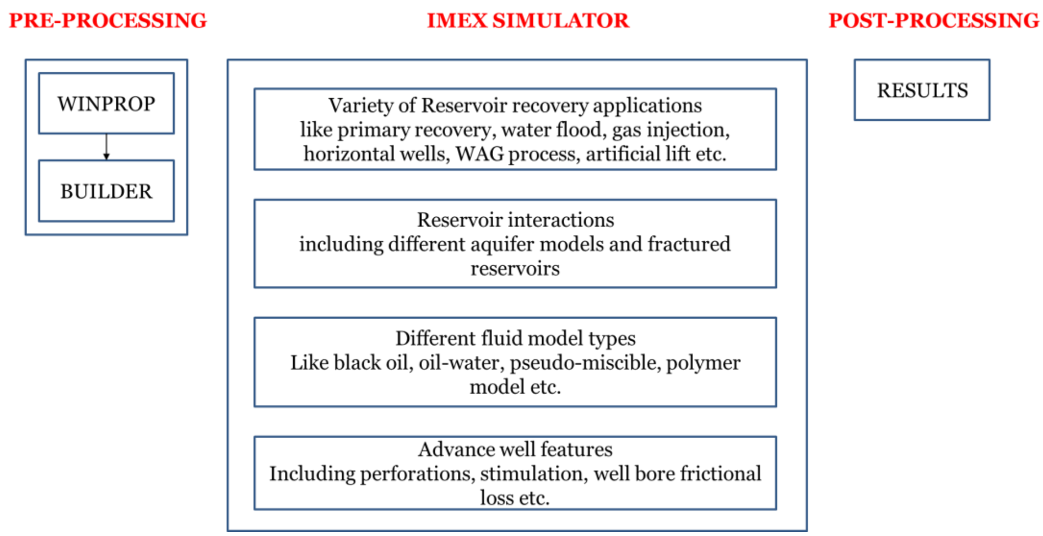


Figure 3.2: Schematic of CMG® IMEX™ Simulator

The Adaptive Implicit Method (AIM), described earlier, was used for solving the simultaneous flow equations, though IMEX™ offers to solve the equations using IMPES and IMPIS. In CMG® IMEX™, AIM is set as the default mode.

In the present study, two distinct reservoirs were used for the purpose of history matching. The first reservoir is a 2-phase (oil and gas), 2-D synthetic reservoir, which is taken from the 10th SPE Comparative Solution Project. The second reservoir is a real 3-phase (oil, gas and water) 3-D reservoir with all the phases flowing simultaneously. For both the cases, the porosity distribution was assumed to be fairly well established and known throughout the reservoirs. The dimensions of the problem are also kept within manageable limits by establishing relative permeability parameters. The only parameter that needs to be calculated for each grid block is the permeability. Here, Non-dominated Sorting Genetic Algorithm-II is applied in solving the optimization problem.

CHAPTER 4

HISTORY MATCHING USING NSGA-II: 2-D SYNTHETIC RESERVOIR

4.1 INTRODUCTION TO GA & NSGA-II

The aim of history matching is to generate a geological model by minimization of the square of data mismatch. Generally, for a reservoir, production data is available over a period of time but the static parameters (porosities and permeabilities) are not known and need to be estimated. Apart from solving history matching manually, which is a highly tedious and time-consuming job, various stochastic soft computing techniques are available to solve it. Here, an evolutionary optimization technique called Non-dominated Sorting Genetic Algorithm-II (NSGA-II), a variation of Genetic Algorithm (GA), is employed to solve the history matching problem. Genetic Algorithm is helpful for solving a problem with single objective function. On the other hand, for problems involving multiple objective functions, NSGA-II is the better option to solve the problem. The reservoir simulator used in the study is CMG® (Computer Modeling Group Limited, Calgary). For the present study, reservoir model is assumed to be black oil model and hence, CMG's black oil simulator called IMEX™ is used for simulation studies.

Genetic Algorithm is a mathematical modelling algorithm which is based on Darwin's 'survival of the fittest'. It is a computer-based search procedure inspired from genetics, which has widespread application. This process utilizes an initial population of individuals (solutions), known as chromosomes, which are further processed where they undergo inheritance, crossover and mutation for several generations that obtains potential solutions. The new generation chromosomes are evaluated based on a fitness function. The concept of GA was conceived by Prof.

John Holland of the University of Michigan, Ann Arbor, USA, in 1975 [138]. The technique commences with one set of several initial solutions which is called as initial population within the constraints of the problems. Each solution of the population is named a chromosome. On the basis of the ideologies of natural selection which is followed by inheritance, crossover and followed by the mutation operations, these undergo consecutive iterations called generations, to generate new chromosomes, with fitness values better than those compared to the previous population. The chromosomes with better fitness values are carried on to the next generation. The fitness of each of these are evaluated with the help of an objective function, known as fitness function, through which individual chromosomes in the search space are characterized based on their performance. The chances of a chromosome to be selected to the next generation increases if it is superior in terms of the fitness value. To maintain the constant population size during iterations/generations, 'lousier' parents and offspring chromosomes may get rejected. After numerous iterations, finally the algorithm converges to that particular chromosomes' set, which has potential to be solutions to given problem.

In general, crossover and mutation operators drives the performance of genetic algorithm. The crossover operator makes random give & take of genetic matter between chosen pair of chromosomes on the assumption that only good chromosomes generates better and fitter chromosomes, closer to the optimal solution. It is not necessary that all the chromosomes undergo crossover. A few of chromosomes from the population remain unchanged. Crossover operation is performed with a crossover probability (P_c) in those chromosomes which are selected for recombination. P_c values are usually specified by the user, following the optimal values in the range of 0.5 – 1.0, as reported in the literature [2]. There are various well-known crossover operators, *viz.*, 1-point, 2-point, *k*-point, uniform crossover operations etc. Chromosomes are later subjected to the mutation operation with a probability, known as mutation probability (P_m). Similar to those for P_c, the optimal values of P_m ranges from 0.001 - 0.05, as reported in the literature [2]. To maintain genetic diversity, the genetic matter of chromosomes get modified during mutation. This helps in avoiding early convergence to local optimum solutions by recalling the lost genetic matter into the population. There are various well-known mutation operators like arithmetic mutation, uniform mutation, jump mutation, creep mutation, swap mutation, etc. The selection of best values of the *computational* parameters (involving the crossover and mutation operations), namely, P_c and P_m, is application-specific and there exist no definite rules to select suitable values [139]. Choosing inappropriate values of P_c and P_m may provoke imbalance in GA's exploration and exploitation process, which further leads to premature convergence that has a bad impact on GA performance. A higher value of P_c abruptly introduces new solutions into the population, thus disrupting optimal solutions. Also, higher value of P_m totally transforms GA into purely randomized search algorithm, but at the same time, to prevent premature convergence, a small mutation is necessary. This process of GA proceeds with generating a new population, until some criterion for termination of the algorithm is satisfied. The mathematics and detailed description of GA can be found in the literature ([140], [141]).

In case of problems with multiple objectives, a set of optimal solutions (known as Pareto-optimal solutions) is obtained instead of one optimal solution. However, it is not at all possible to claim that one of these Pareto-optimal solutions is better than the other, without any further information. For moving towards the true Pareto-optimal region, non-dominated sorting algorithm (NSGA) was employed which uses a ranking selection method that emphasizes good points and a niche method to maintain stable sub-populations of good points [142]. However, to overcome the problems like computational complexity and lack of elitism associated with it, NSGA-II was introduced [143]. Elitism can be associated to the property of highly qualified individuals or chromosomes that possess superiority regarding to the objective function. In NSGA-II, all the individuals are arranged by a Pareto relationship with the help of a 'fast non-dominated sorting algorithm' and a non-dominated index assigned to them. If individuals has the same rank, diversity can be measured by a 'crowding distance'.

4.1.1 Workflow of NSGA-II

The overall workflow of NSGA-II is given in Fig. 4.1. It starts with feeding values of the population size, maximum number of generations, crossover and mutation probabilities and ends when a termination criterion is reached.

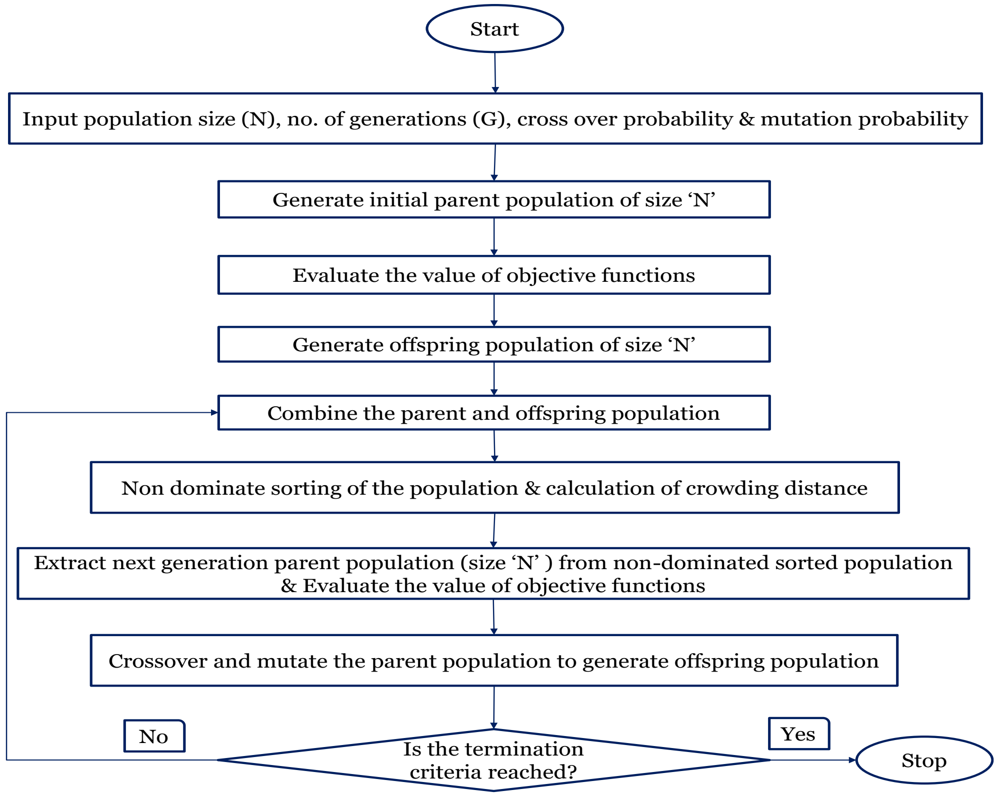


Figure 4.1 NSGA – II Workflow

The technique uses fast non-dominated sorting algorithm that sorts the individuals [144]. Methodology of sorting is given below. Let us consider 'P' represents the population and 'a' and 'b' are individuals, n_a is the count of solutions dominating the solution 'a', S_a is the set of solutions that the solution 'a' dominates and NDF_i is the non-dominated front in the population. The algorithm is as follows:

For each $a \in P$

$S_a = \emptyset$

$n_a = 0$

For each $b \in P$

If $a < b$ then //If a dominates b

$S_a = S_a \cup \{b\}$ //Add b to the set of solutions dominated by a

else if $b < a$ then //If b dominates a
$n_a = n_a + 1$ //Increment the domination counter of a
If $n_a = 0$ //a belongs to the first front
$a_{rank} = 1$
$NDF_1 = NDF_1 \cup \{a\}$
$i = 1$ //Initialize the front counter
while $NDF_1 \neq \emptyset$
$Q = \emptyset$ //Used to store members of next front
For each $a \in NDF_i$
For each $b \in S_a$
$n_b = n_b - 1$
If $n_b = 0$ then //b belongs to the next front
$b_{rank} = i + 1$
$Q = Q \cup \{b\}$
$i = i + 1$
$NDF_i = Q$

Following the algorithm, every individual/solution is assigned with a non-dominated rank and based on this rank, the entire population can be divided into many non-dominated fronts. There may be more than one individual in a non-dominated front which means all of them have the same non-dominated rank. The lower is the non-dominated rank, the better is the chance for it's getting into the next generation. All the low ranked individuals will be entering the next generation until it exceeds the population size. If the entry of all the similar ranked individuals into the next generation is not possible (i.e., if the population size is exceeded), the crowding distance comes into the picture. Crowding distance distinguishes individuals which are in the same non-dominated front. Crowding distance is the mean length of the largest rectangle in the area that contains the individual itself. The algorithm below shows the calculation of the crowding distance.

Input Γ \\ Γ is the set of individuals in a non-dominated front
$l = |\Gamma|$ \\ l is the number of individuals in Γ
For each i, set $\Gamma[i]_{distance} = 0$ \\ initialize distance
For each objective m
Γ = $sort$ (Γ,m) \\ sort using each objective value

$\Gamma[1]_{distance} = \Gamma[l]_{distance} = \infty$ \\ so that boundary points always get selected

For $i = 2\ to\ (l-1)$

$$\Gamma[i]_{distance} = \Gamma[i]_{distance} + \frac{(\Gamma[i+1].m - \Gamma[i-1].m)}{f_m^{max} - f_m^{min}}$$

where $\Gamma[i].m$ refers to the m^{th} objective function value of the i^{th} individual in set Γ, f_m^{max} and f_m^{min} are maximum & minimum values for the m^{th} objective function.

Each individual in the population is now associated with a non-domination rank (i_{rank}) and a crowding distance ($i_{distance}$). A partial order relationship is defined, as per which, an individual with lower non-domination rank will be selected over another individual with higher rank and the individual associated with greater crowding distance will be chosen over another individual when both individuals are ranked the same. This new set of parent population is then used for selection, crossover and later mutation for generating offspring population.

4.1.2 Generation of the Initial Population

Initial population is crucial to start with the proceedings. In the problems of history matching, the populations generated represent the reservoir ensembles or the realizations, which contain the properties of reservoir rock like porosity and permeability. Unlike general problems of minimization, it is not appropriate to choose a random set of solutions as initial population for history matching. Hence, geostatistical methods are used in order to generate initial population ([1], [145]). These realizations honor the variogram and spatial correlation of the reservoir properties. Stochastic conditional simulation, one of the geostatistical methods, is found out to honor the observations at the well locations [121]. Here, the initial realizations were generated using GSLIB's VISIM. VISIM is a sequential simulation code based on GSLIB ('Geostatistical Software LIBrary', Stanford Center for Reservoir Forecasting, Stanford University) for sequential Gaussian and direct sequential simulation with histogram reproduction [146]. VISIM can be used to generate samples of the a *posteriori* distribution of a linear inverse problem.

4.1.3 Inputs to the CMG® Simulator

A reservoir model is created by integrating many inputs, *viz*., geological model that describes the structure of reservoir, gross-thickness, fluid model (PVT properties), permeability and porosity distribution maps, description of simulation grid, rock fluid model (saturation, relative permeabilities), faulting, aquifer modeling, fluid contact, production and completion history.

Grid selection and size also play an important role to get accurate results. To ease the computational complexities, a reservoir may be divided into a number of 2-D or 3-D grid blocks, which can be non-orthogonal, orthogonal, cylindrical, radial, Cartesian, and depending on the extent of the reservoir. Grid blocks if chosen in larger number make the algorithm slower whereas a small number of grid blocks leads to inaccurate results. Grid size, also an input to the simulator, is problem-dependent and is deliberated separately for investigated case studies.

Distribution of faults in the reservoir greatly impacts behavior of reservoir. The presence of faults not only affects the petro-physical properties of the rock but also alters the flow pattern in sedimentological flow blocks. Hence, faults and its' details should also be specified in the model.

4.1.4 NSGA-II Flowchart for History matching

As described in earlier sections, generation of initial population using GSLIB and developing a reservoir model with the help of various parameters for giving input to CMG® IMEX™ Simulator are the unique tasks for History matching problem. The objective function for the problem is formulated and subsequently evaluated based on the field production data obtained over a period of time and the production data obtained from the simulator based on the reservoir model developed. The complete flowchart incorporating these in NSGA-II methodology is as given in the figure 4.2

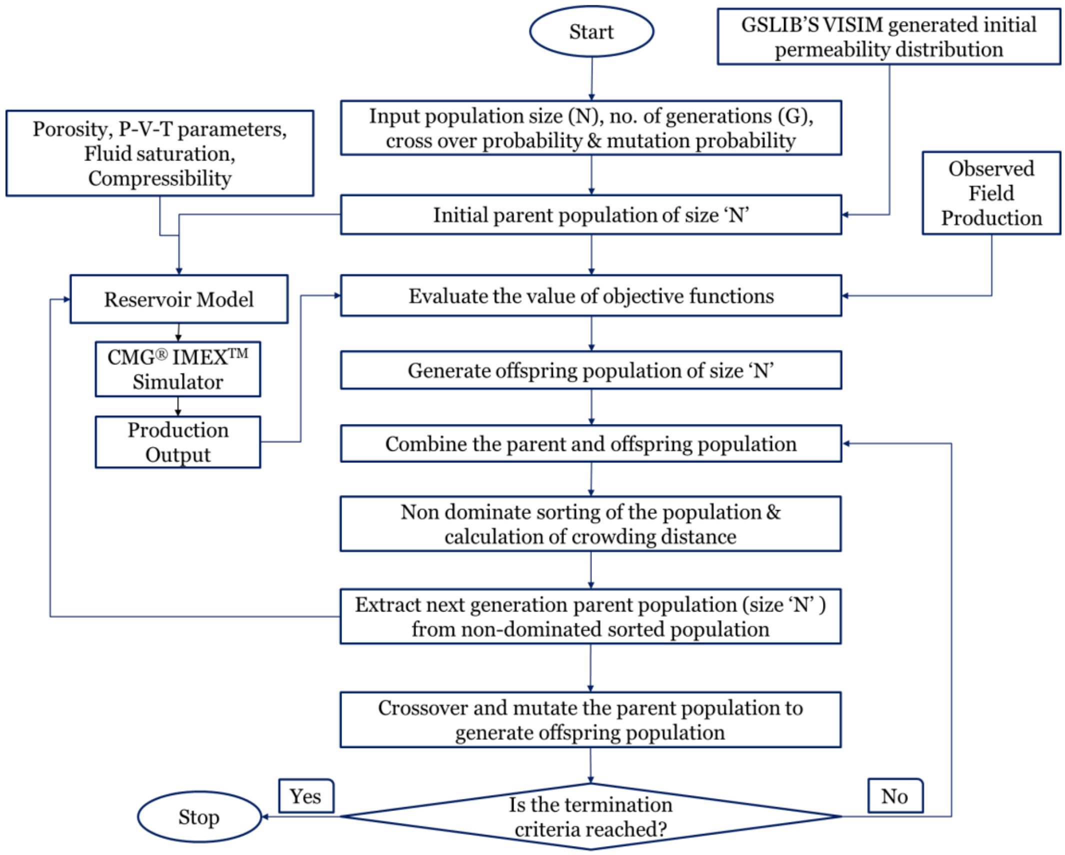


Figure 4.2: History Matching Problem: NSGA – II Flowchart

4.2 HISTORY MATCHING OF A 2-D SYNTHETIC RESERVOIR

It is always apt to test any proposed methodology on relatively-trivial data before applying it to real data. In this case, it is essential to validate the proposed history matching scheme and methodology along with the developed NSGA-II code. Hence, a 2D synthetic reservoir problem was chosen for the purpose of validation [103]. As the synthetic reservoir model was built with a known permeability distribution, the problem suits our purpose. Production can be evaluated with known parameters and history matching can be done.

4.2.1 Description of Synthetic Reservoir

The synthetic black oil reservoir, chosen for the validation studies, is a 2-Dimensional model which consists of 20 layers in the Cartesian coordinate system. Entire reservoir volume is divided into $100 \times 1 \times 20$ grid blocks with each grid block measuring 25ft × 25ft in dimension. Only two phases (oil and gas) are existing in the reservoir. Without any faults present, the reservoir model is considered to be completely oil-saturated (without connate water). There are 3 wells present in the reservoir – 1 (I-1) injector well located at grid block (50, 1, 1) and 2 producers (W-1 and W-2) placed on either side of the injector, symmetrically, as shown in the Fig 4.3.

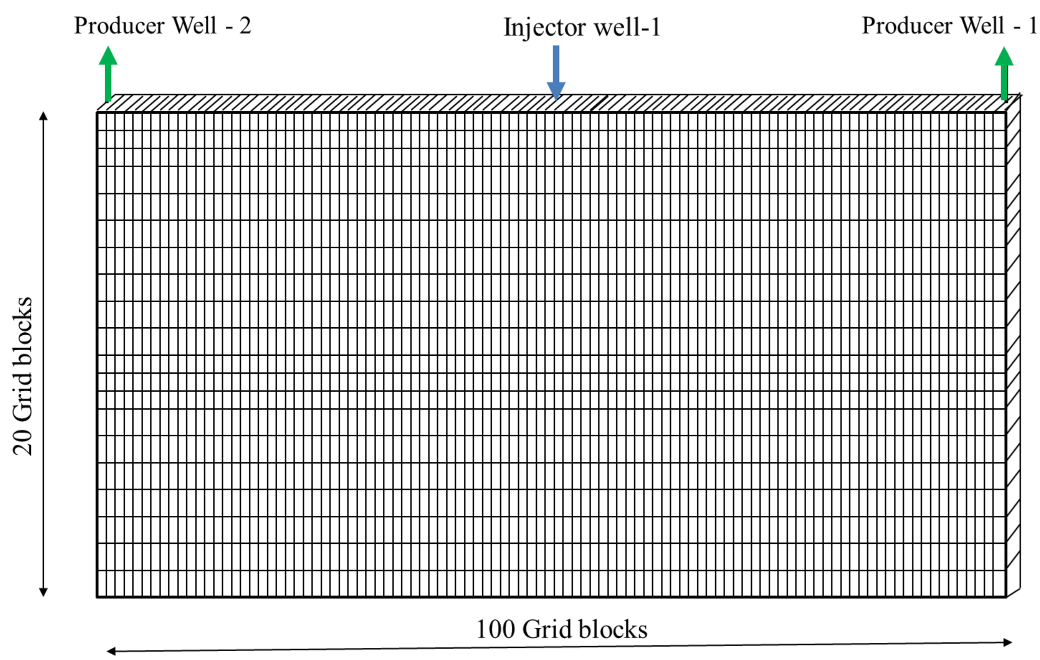


Figure 4.3: Schematic of synthetic reservoir

All the three wells are perforated through 20 layers of the reservoir. It is assumed throughout all the layers of the reservoir that it has a constant porosity of 0.2 with permeabilities varying in the *i* direction. The permeability values are assumed to be equal in *i*, *j* and *k* directions. The true permeability data of the reservoir is given, from which the field production history for a period of 8 years is calculated. In addition to the existing wells, two core holes at locations (25, 1) and (75, 1) covering all the 20 layers, are considered to be drilled vertically. The values of permeability at core hole locations and wells are assumed known. Values of permeabilities in remainder of 1900 grid blocks is to be found out for history matching.

4.2.2 Optimization problem formulation

The fitness of the chromosome is evaluated with the help of an objective function. The formulation of objective function for history matching targets to minimize (lessen) the mismatch (discrepancy) between the field real production and simulated production data. Problem should have a minimum of two objective functions, to apply NSGA-II. However, a standard practice of using two identical objective functions is followed, to apply NSGA-II for this case [147]. The objective function for the case study targets to minimize the disparity between observed fluid production from Well-1 and simulator output and is expressed as below.

$$Q = \sum_{k=1}^{32} \left(\frac{d_{k,oil}^{O} - d_{k,oil}^{S}}{d_{k,oil}^{S}}\right)_{Well-1}^{2} + \sum_{k=1}^{32} \left(\frac{d_{k,gas}^{O} - d_{k,gas}^{S}}{d_{k,gas}^{S}}\right)_{Well-1}^{2} \tag{4.1}$$

Here, d^{0} is the field observation and d^{S} is the simulated (model) value in terms of quarterly oil and gas production rate & '*k'* is the time period that represent 32 quarters (8 years) of production.

The problem has 2000 variables, which are the values of permeability at 2000 locations, of which, 100 values of permeability at predefined 100 locations are set back to their original values, making the problem has net 1900 variables. The lower bound of the permeability is set to 0.01 mD and the upper bound of the permeability is fixed as 1000 mD. The optimization problem has no constraints.

4.2.3 Selection of GA Parameters

For testing of NSGA-II, a synthetic 2-D black oil reservoir model is chosen. The standard genetic operators such as recombination, mutation and reproduction operators are employed. Tournament selection is employed as the selection or reproduction operator for choosing fittest member among the population and moved to the mating pool. Uniform *k*-point crossover is employed to carry out crossover operation in the chromosomes. The mutation in chromosomes is induced by uniform mutation operator to generate new populations. The studies are carried out with different sets of values of the crossover and mutation probabilities. The different sets of values of (P_c, P_m) used are (0.95, 0.02) and (0.98, 0.01).

4.2.4 Inputs to the CMG® Simulator

The properties of the synthetic reservoir are given in Table 4.1

Table 4.1: Properties of the Synthetic Reservoir

Property	Value
Initial Reservoir pressure (MPa)	0.69
Porosity	0.2
Datum depth (m)	0.0
Oil density (kg/m^3)	700
Gas density (kg/m^3)	1
Oil viscosity (cP)	1.0
Gas viscosity (cP)	0.01

4.2.5 Grid Selection of 2-D Reservoir

A 2-D grid of dimensions 100 × 20 was imposed on the reservoir, which divides the entire reservoir into 2000 grid blocks (as shown in Fig. 4.3), each grid block spanning an area of 7.62 m × 7.62 m. The porosity was given to be constant throughout the reservoir. The exercise of History matching for this case is required to find out the values of permeability for all the grid blocks, with the given production history. Here, in the formulation of GA there are chromosomes whose length of the string is 2000 and each element in the string represents the permeability value of a grid block. Also, values of permeability at well locations (wells drilled vertically all over 20 layers, hence, for 100 grid blocks) are known and therefore should not change for each generation. A population size of 40 was chosen for the case study and therefore 40 initial realizations or ensembles were produced by application of conditional direct simulation in VISIM software.

4.2.6 Generation of Initial Population

A population size of 40 initial realizations or ensembles for the 2D synthetic reservoir is generated using GSLIB's VISIM. The simulation of these realizations is conditioned to the well location and core hole data. Anisotropic variogram is used in generating these realizations. The initial 40 ensembles generated by VISIM is shown in Figure 4.4. One of them is shown vividly in Figure 4.5.

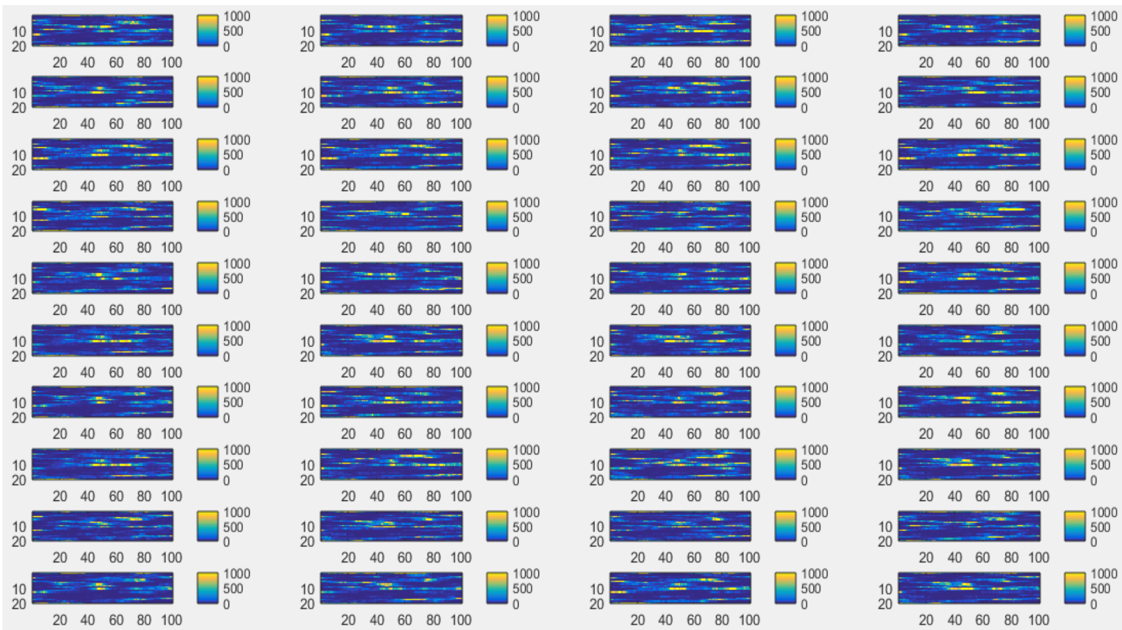


Figure 4.4: Initial permeability ensembles (40 Nos.) of the 2-D synthetic reservoir

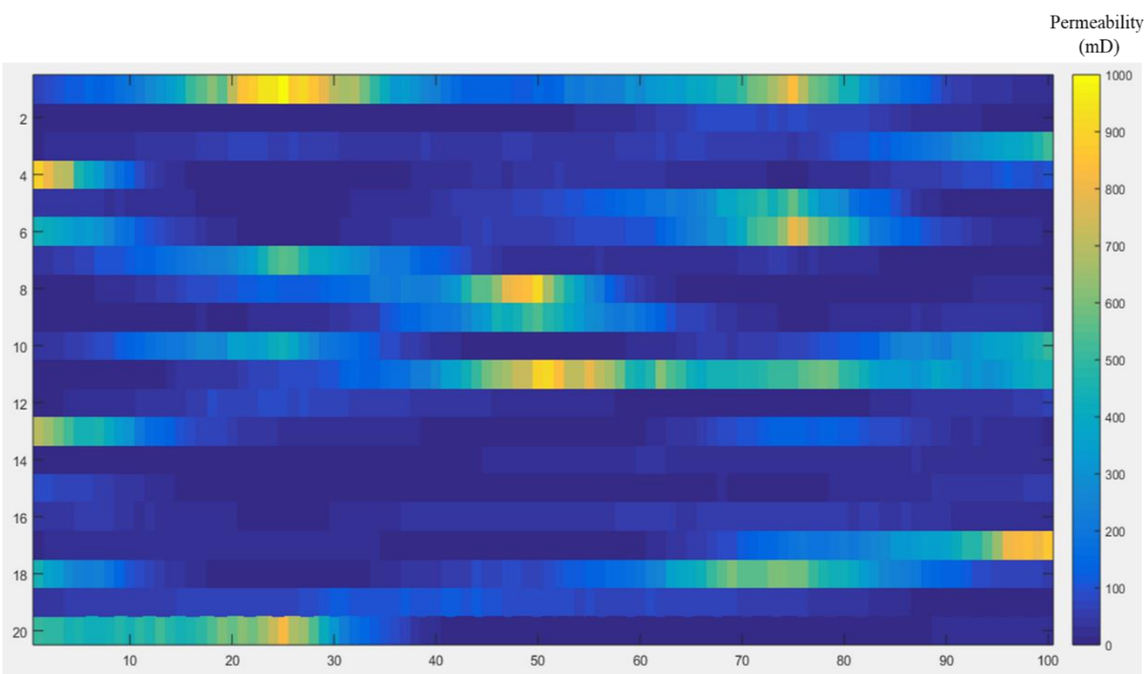
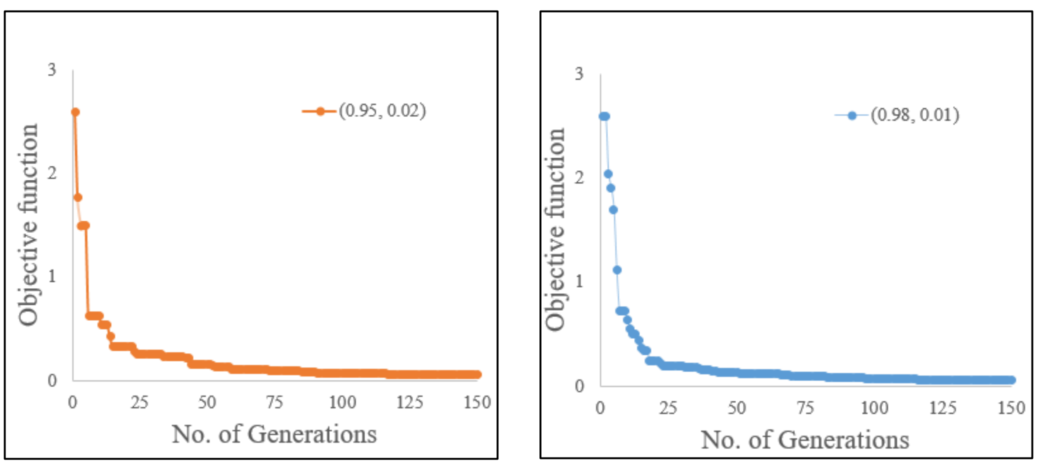


Figure 4.5: Initial permeability ensemble of 2-D synthetic reservoir

4.3 RESULTS AND DISCUSSION

NSGA-II is applied to the problem with population size of 40 and two different sets of values of (P_c, P_m), *viz.*, (0.95, 0.02) and (0.98, 0.01) for 150 generations. Starting with the same initial population generated using VISIM, fluid production rates are calculated by the simulator and the objective function is evaluated. It is understood that better history-matched models are characterized with lower values of the objective function.

The value of the fitness function of the initial realization calculated is Q_{min} = 2.5978. NSGA-II with (P_c, P_m) = (0.95, 0.02) produced the value of the objective function, Q_{min} = 0.5563 at the end of the 150th generation. NSGA-II with (P_c, P_m) = (0.98, 0.01) produced the objective function as Q_{min} = 0.5097 at the end of the 150th generation. For both these cases, Figures 4.4a and 4.4b show the variation of the objective functions with the generation. Here, it is evident that the initial ensembles of permeability move towards the real map as the number of generations increase and that with (P_c, P_m) = (0.98, 0.01), a better history matched model is obtained.



(a) (b)

Figure 4.6: Improvement of the value of the objection function with generation number (a) (P_c, P_m) = (0.95, 0.02) (b) (P_c, P_m) = (0.98, 0.01)

The best history matched model obtained from NSGA-II is compared with the measured values of oil and gas production. As evident from Figure 4.5, oil production history matches quite well with observed values and the history match of gas production is quite reasonable.

(a)

(b)

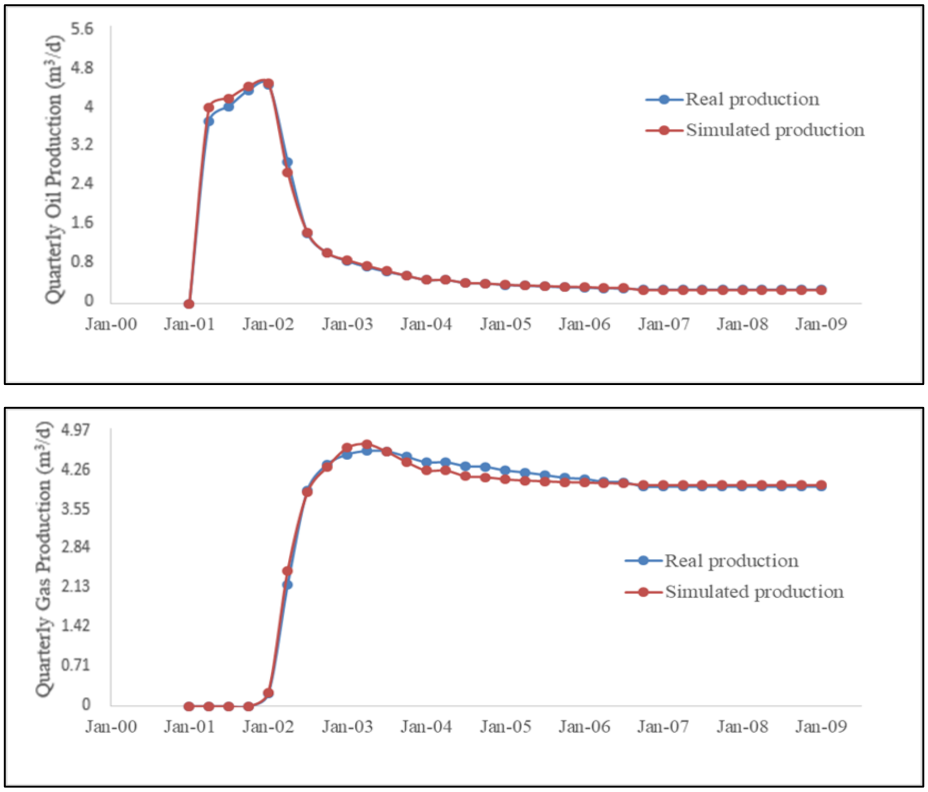


Figure 4.7: NSGA-II: Final history match

(a) Quarterly oil production (m^3/day), (b) Quarterly gas production (m^3/day)

4.4 REMARKS

For 2-D synthetic reservoir, history matching with the application of NSGA-II has been validated successfully. Similar to other variants of GA, NSGA-II has showcased its ability in producing history match for gas and oil production from Well-1. The study here is confined to history matching the production from only Well-1, even though there are 2 production wells in this case as the motive of this case study is validating the NSGA-II code for history matching. The history match obtained through NSGA-II showed as good a match as that offered by Chitra *et al.* (2010) using EnKF [103]. Hence, NSGA-II for history matching of reservoir is validated successfully.

CHAPTER 5

HISTORY MATCHING USING NSGA-II: 3-D REAL RESERVOIR

In this research, an evolutionary optimization technique called Non-dominated Sorting Genetic Algorithm-II (NSGA-II), a variant of Genetic Algorithm (GA) that is applied for multi objective problems, is employed to solve the history matching problem. As we have validated the application of NSGA-II successfully for history matching a black oil model reservoir, the case study, taken from the literature [2], is also a black-oil model. As the total pressure drop is found to be less than 10% of the initial pressure over its entire production period of 10 years, it was sufficient to use black-oil model for flow simulation. The structural details and reservoir parameters are described in next section.

5.1 CASE STUDY DESCRIPTION

A real reservoir is chosen, for which nine years of production history is available. NNW-SSE is the direction of the field structure. On either sides, fault separates the structure from the adjoining lows. Fault surrounding the reservoir is non-communicating. The field is composed of three layers of sandstone and there are six producing wells. Reservoir pressure was initially recorded as 14.12 MPa at 1397m. It was reported that there are two aquifers, one towards the N-W side and the other towards the narrowest region of reservoir in Layer-3. The field details of reservoir are tabulated in Table 5.1.

The producer wells, W-3 & W-5, extend from layer 1 to layer 2 whereas wells W-1, W-2, W-4 & W-6 extend from layer 2 to layer 3 (referred to as, for example, well W-3 *being perforated in* layers 1 and 2). The schematic of these layers and well perforations are shown in Fig 5.1.

Table 5.1 Field observations of the real reservoir

Initial reservoir pressure (MPa)	14.12 at 1397 m.
Quantity of reserved Oil in place (MMt)	2.47
Cumulative Oil production till Sep' 09 (MMt)	0.72

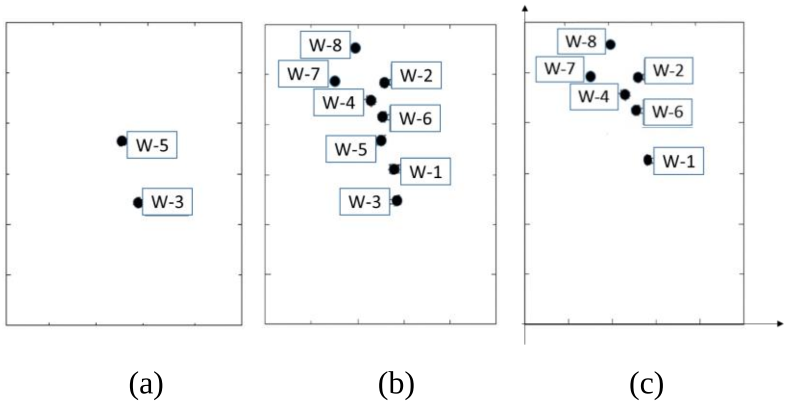


Figure 5.1: Schematic of the three layers and the six wells (extending over the three layers). (a) layer 1, (b) layer 2 and (c) layer 3

The production in wells is occurring at pressures above bubble point pressure and hence gas to oil ratio (GOR) is in the range of 30-35 v/v. Hence the model shows constant producing GOR. Figure 5.2 shows the grid bottom structure of the reservoir.

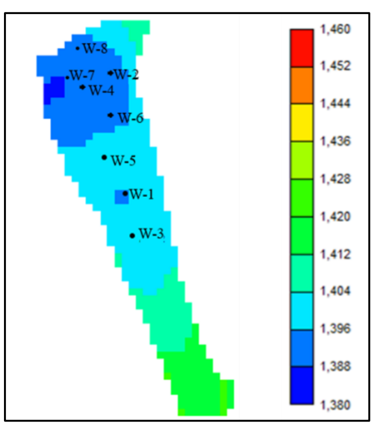


Figure 5.2: Grid bottom structure of real reservoir

Production has commenced through W-1 and W-2 from Feb'00 and Dec' 00 respectively and the initially recorded reservoir pressure at W-1 was 14.12 MPa at 1385 m. The cumulative productions of oil, water and gas from W-1 till Sep'09 are 0.156 MMt, 7.2 MMm^3 and 8.1 MMm^3 respectively. Subsequently, other wells were drilled and were allowed for hydrocarbon production in distinct years till 2009. Two more wells (W-7 and W-8) were drilled and were put on production in Jan' 09. However, production data of 70 months (from the period 2000 – 2005) was only used for history matching and the remaining production data was used for validating.

Each of the three layers are divided into a computational grid, with each grid point being associated with a value of the porosity and permeability. Here, each layer is divided into a 2-D grid (in the directions of x and y), with $\Delta x = 100$ m and $\Delta y = 100$ m. There are 50 grid blocks in the x direction and 60 grid blocks in the y direction. Every grid block is associated with a value of the porosity and a permeability. Thus, there are 3,000 values of each of these in each of the three layers, making it 9000 values of each i.e. porosity and permeability. The permeability is given as 300 mD for layer 1 and given at well locations for other layers. The porosity is constant throughout a given layer i.e. 0.21, 0.22 and 0.23 for the layers 1, 2 and 3 respectively.

5.1.1 Optimization problem formulation

The objective of this case study is to find the optimal permeability distribution in layers 2 and 3 that minimizes the discrepancy between the simulator predictions and actual observations. The objective function, similar to that formulated for synthetic reservoir case, is formulated considering the time period, field observations and number of wells. Here, the field data comprises of oil production rate , GOR , water cut & BHP taken from all the six producers for 70 months of production history. Hence the objective function is expressed as

$$Q = \sum_{i=1}^{N_w} \sum_{k=1}^{N_q} \left(\frac{d_{k,oil}^{O} - d_{k,oil}^{S}}{d_{k,oil}^{O}}\right)_i^2 + \left(\frac{d_{k,GOR}^{O} - d_{k,GOR}^{S}}{d_{k,GOR}^{O}}\right)_i^2 + \left(\frac{d_{k,WC}^{O} - d_{k,WC}^{S}}{d_{k,WC}^{O}}\right)_i^2 + \left(\frac{d_{k,BHP}^{O} - d_{k,BHP}^{S}}{d_{k,BHP}^{O}}\right)_i^2 \qquad (5.1)$$

Here, N_w (= 6) is the number of wells, N_q (= 70) is the number of months, d^0 is the field observation and d^S is the corresponding simulated (model) value in terms of monthly oil production rate (OIL), gas-oil ratio (GOR), water cut (WC) and bottom hole pressure (BHP). Value of the objective function 'Q' was a minimized using NSGA-II & search was ended when the values of 'Q' was essentially same in successive iterations.

The problem has 6000 variables, which are the values of permeability at 6000 locations in 2 layers, of which, 14 values of permeability at predefined 14 locations are set back to their original values. The lower bound of the permeability is set to 0.01 mD and the upper bound of the permeability is fixed as 1000 mD. The optimization problem has no constraints.

5.1.2 Inputs to the CMG® Simulator

Any reservoir model is built by combining parameters viz. geological structure, petrophysical data, grid definition (type and size), properties of reservoir fluid, initial conditions, well completion data, P-V-T properties etc. The table below gives us the model parameters and PVT properties that are fed to CMG® Simulator to build the model.

Table 5.2 Reservoir Model parameters and PVT properties

Reservoir Temperature (K)	369.95
Initial Reservoir Pressure (MPa)	14.12
Datum depth (m)	1400
Depth of water oil contact (m)	1397 – Layer 1; 1401 – Layer 2 1402 – Layer 3

Bubble Point Pressure (MPa)	8.04
Density of Oil (kg/m^3)	850
Viscosity of Oil (cP)	0.98
Specific Gravity of Gas	0.95
Gas-Oil Ratio in the Initial Solution	32 v/v
Volume Factor of the Oil Formation	1.2 Reservoir barrels/stock tank barrel

The relative permeability information have been generated by applying Corey's correlation within the simulator [148]. The porosity values and measured permeabilities at well locations are given in Table 5.3. The porosity is constant throughout a given layer i.e. 0.21, 0.22 and 0.23 for the layers 1, 2 and 3 respectively. The permeability is given as 300 mD for layer 1 and given at well locations for other layers. The other data required for building the model are included in Appendix.

Table 5.3 Values of the Porosity and Permeability of the Three Layers

Layer	Porosity throughout the layer	Permeability at a location	
		Location (*x*, *y*) (m)	mD (x 1000 μm^2)
Layer 1	0.21	Throughout the layer	300
Layer 2	0.22	(2020.866, 5101.895)	533.2
		(2516.858, 4935.464)	732.7
		(2181.874, 4702.655)	412.7
		(1764.404, 4607.200)	394.1
		(2569.139, 4357.980)	329.7
		(2468.298, 3735.591)	420.0
		(2793.034, 3191.109)	446.8
		(2915.995, 2620.678)	446.7

Layer 3	0.23	(2025.845, 5091.209)	533.2
		(2511.532, 4924.293)	732.7
		(2181.381, 4692.627)	412.7
		(1767.349, 4603.087)	394.1
		(2564.105, 4350.277)	329.7
		(2790.579, 3187.187)	446.8

5.1.3 Grid Selection of Real Reservoir

The CMG simulator generally uses 50m x 50m sized block grid on the reservoir. This will result in 36000 grid blocks (100 x 120 x 3) for the present case study. However, a grid of coarse scale was utilized, in the present case study, to limit the dimensionality of GA variables, resulting in 9000 (50 x 60 x 3) grid blocks. As mentioned earlier, each grid block is associated with the values of porosity and permeability. Since the porosity values are known for all the layers and the permeability values are known for first layer alone, the objective of this study aims at estimating the permeability distributions in layers 2 and 3. This necessitates to estimate 5986 values of permeability disregarding the already known 14 values of permeabilities in layers 2 and 3. An attempt was also made to reduce the no. of variables by non-linear interpolation through SGSIM. Methodology and results of both the above cases - case (a) and case (b), with 5986 variables and with reduced no. of variables respectively, are described below.

5.1.4 Generation of Initial Population

In this case, initial population was generated with the help of mGstat, a geostatistical toolbox from MATLAB®, that has interfaced to the SGeMS. The initial ensembles/realizations were generated by employing the Sequential Gaussian Simulation (SGSIM) which obey the histogram and spatial variations of the real reservoir. SGSIM determine every distribution of petrophysical properties under multivariate Gaussian model. Each grid block permeability in the ensembles were estimated using a Gaussian variogram model with a sill value 1 and correlation range of 20 grid blocks. With the chosen population size as 30, a set of 30 initial ensembles were generated using SGSIM which honor the values of permeability at well locations. Case (a) involves generation of 6000 variables per realization. The dimensionality of the problem can reduced by using a network of pilot points and geo-statistical interpolation methods [149]. Following the same, the number of variables are reduced for Case (b). Out of 6,000 points in layers 2 and 3, forty *pilot locations* are chosen. Of these forty, fourteen are at the positions of well locations given in Table 5.3 and the remaining 26 locations (13 in each layer) are chosen randomly, which are spread over the reservoir and whose locations are given in Table 5.4. Hence, the problem is now reduced to estimating 26 permeabilities. The initial population values of the permeabilities at these 26 locations are chosen by the NSGA-II code and the remaining 5,960 values are determined by interpolation through SGSIM.

Table 5.4 Locations (x, y, in m) of the pilot points

Layer 2	Layer 3
(100, 600)	(100, 400)
(500, 900)	(500, 700)
(800, 600)	(600, 800)
(900, 1000)	(1200, 1100)
(1200, 1000)	(1600, 1500)
(1200, 1100)	(1600, 3600)
(1500, 1400)	(1900, 2000)
(1600, 1800)	(2400, 2300)
(2900, 2600)	(2500, 4100)
(3800, 5800)	(3200, 500)
(4000, 2000)	(3400, 3600)
(4400, 4600)	(4600, 4800)
(4700, 5800)	(4800, 5700)

5.2 RESULTS AND DISCUSSION

5.2.1 Results for Case (a)

NSGA-II is applied to the problem of 6000 variables and population size 30 with three different sets of values of (P_c, P_m) *viz.* (0.95, 0.02), (0.98, 0.01) and (0.99, 0.005) for 150 number of generations. Starting with the same initial population, fluid production rates are calculated by the simulator and objective function is evaluated. Values of objective function for the initial ensembles for both the sets of (P_c, P_m) are equal as chosen initial population is same and are given in Table 5.5. The minimum, maximum and mean objective function values were found to be 1022.39, 1175.23 and 1115.53 respectively. The observed values *viz.* oil production rate, water cut, GOR and BHP are plotted against the simulator output values in figure 5.3. It is evident that first generation simulator output values of oil production rate and GOR shows a reasonably good match with those of the observed field values but water cut and BHP shows significant variations.

Table 5.5 Values of Objective function (Q) for 30 initial ensembles for Case (a)

Ensemble No.	Q	Ensemble No.	Q
1	1148.08	16	1119.32
2	1175.23	17	1072.69
3	1116.04	18	1110.35
4	1090.09	19	1106.19
5	1083.68	20	1113.33
6	1128.55	21	1062.67
7	1105.83	22	1143.14
8	1150.94	23	1135.25
9	1134.52	24	1144.29
10	1122.23	25	1119.41
11	1132.88	26	1123.46
12	1149.12	27	1119.48
13	1093.68	28	1098.69
14	1088.57	29	1115.96
15	1139.69	30	1022.39

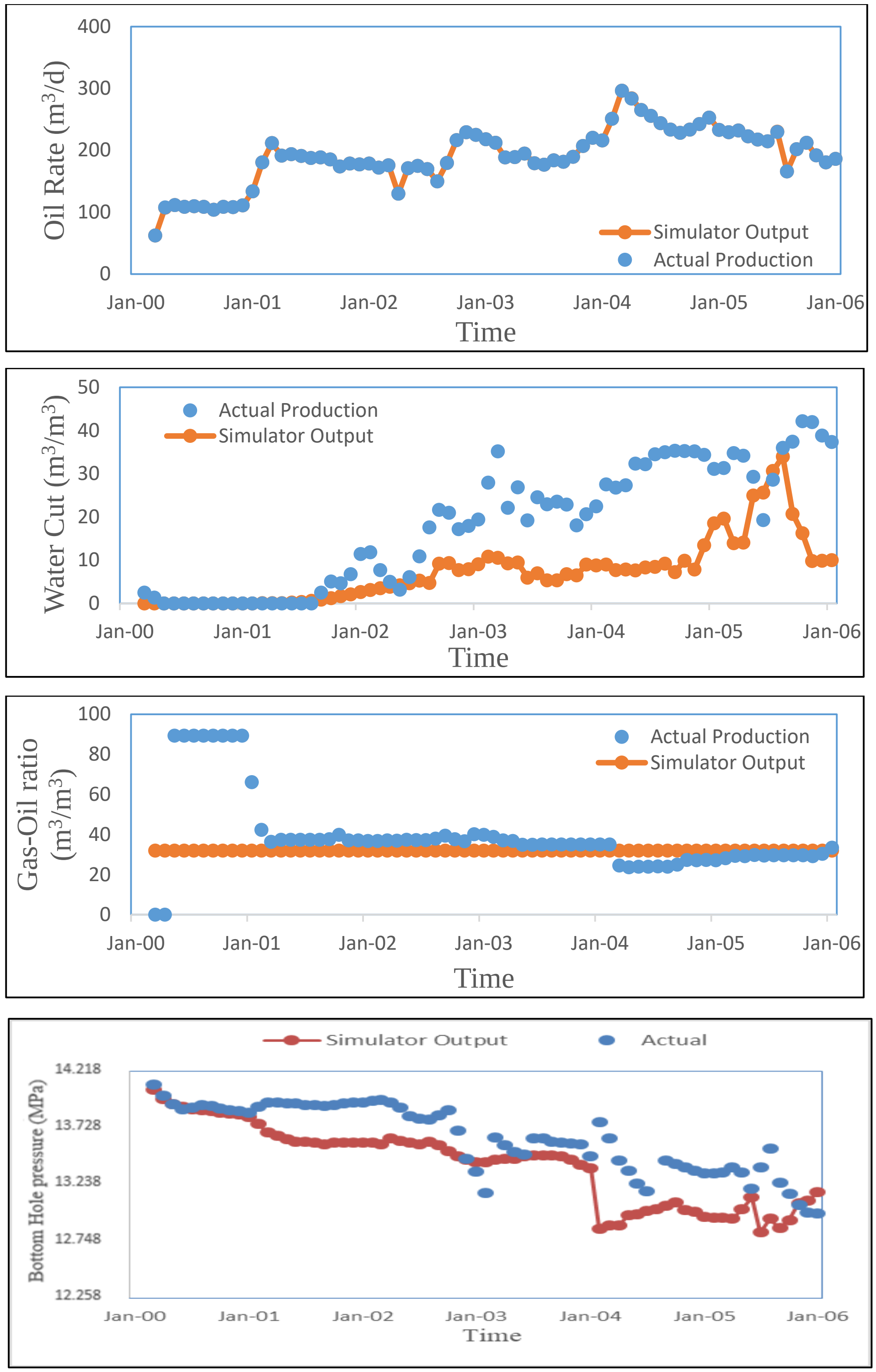


Figure 5.3 Case (a) - Comparison of simulator output of best initial ensemble (before optimization) with observed field values for (a) Oil rate (b) Water cut (c) GOR and (d) BHP

The variation of ‘Q’ with generation for the three sets of values of (P_c, P_m) *viz.* (0.95, 0.02), (0.98, 0.01) and (0.99, 0.005) is given in figure 5.4. The NSGA-II search was terminated after 150 generations that resulted in Q_{min} = 208.68, 241.29 and 214.61 for (P_c, P_m) = (0.95, 0.02), (0.98, 0.01) and (0.99, 0.005) respectively.

The better convergence of Q is obtained for (P_c, P_m) = (0.95, 0.02) and hence the permeability distribution corresponding to (P_c, P_m) = (0.95, 0.02) is used to evaluate the production. The value of Q_{min} varied from 1022.38 to 208.68 after 150 generations. The significance of this variation can be seen when simulator output values of water cut and BHP after 150 generations is compared with the actual production values and initial generation simulator output values.

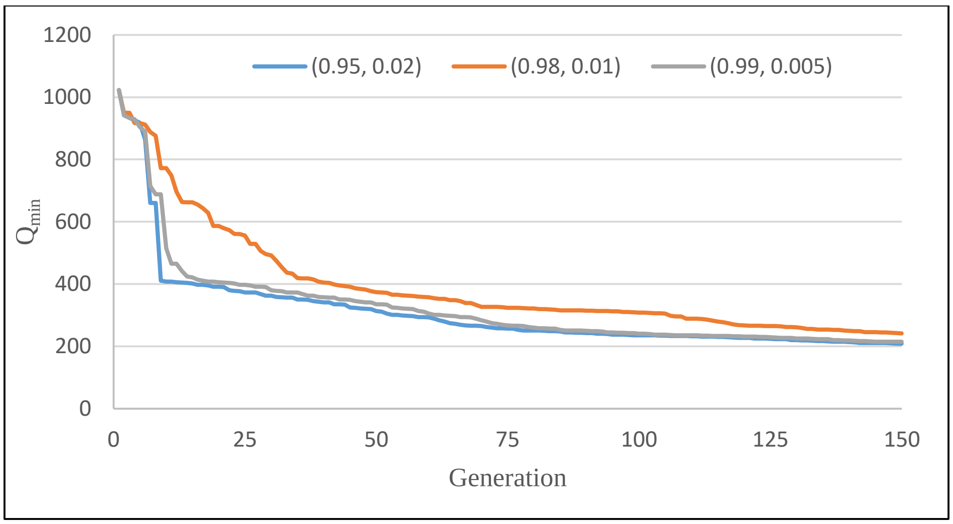


Figure 5.4: Variation of objective function ‘Q_{min}’ with generations for (P_c, P_m) = (0.95, 0.02), (0.98, 0.01) and (0.99, 0.005) for case (a)

From the figure 5.5 (b) and (d) given below, it is evident that the water cut and BHP matched better to field data except for the initial higher GOR. Oil production rate and gas-oil ratio continues to show good match upto 150 iterations, as clear from figure 5.5 (a) and (c).

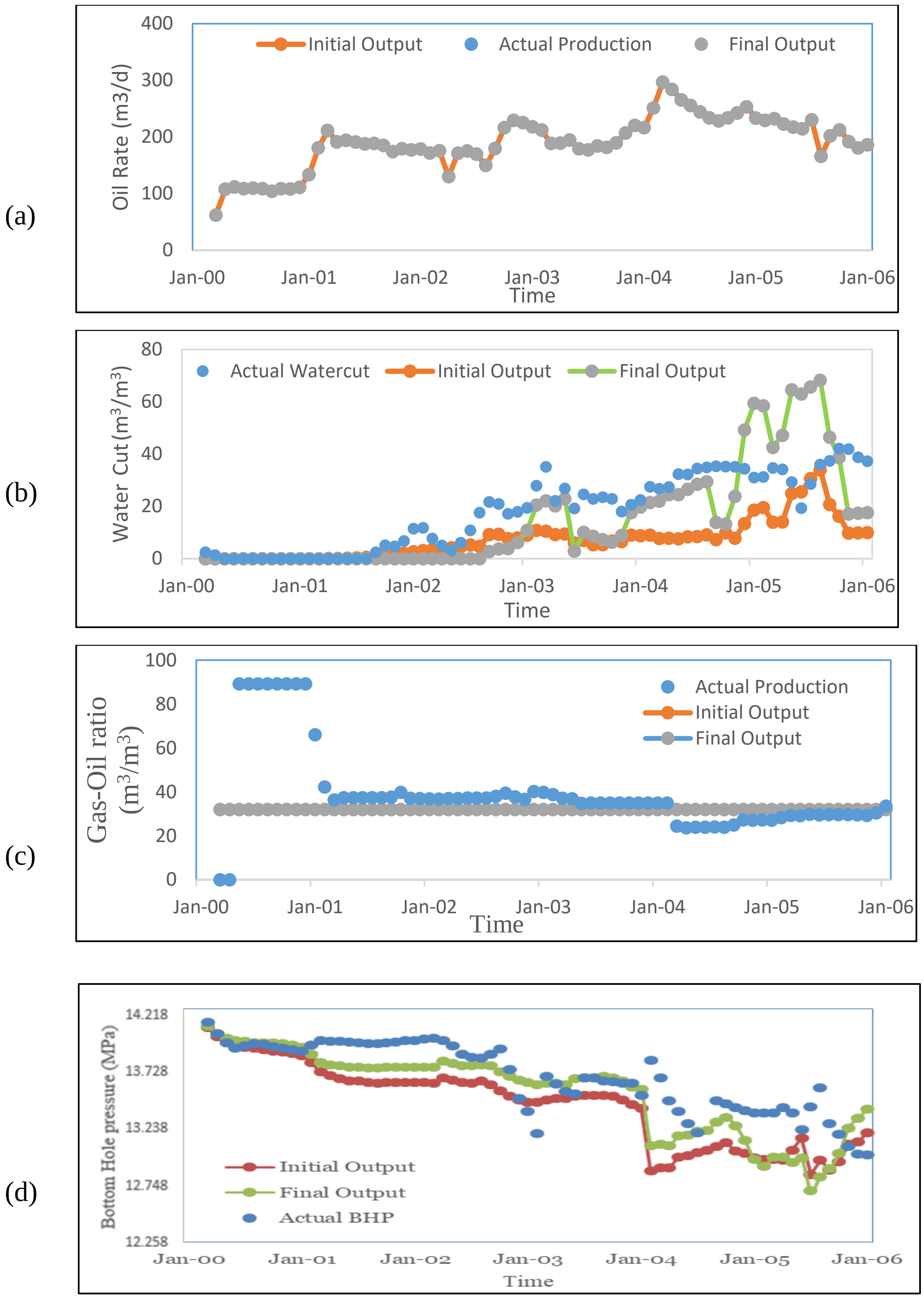


Figure 5.5 Case (a) - Comparison of simulator output of best final ensemble (after optimization) with observed field values and best initial ensemble (before optimization) for (a) Oil rate (b) Water cut (c) GOR and (d) BHP

5.2.2 Results for Case (b)

As mentioned earlier, of 40 pilot locations chosen, 14 are the well locations whose permeability data is known and 26 others are chosen randomly, well spread over the reservoir. NSGA-II is applied to the problem of 26 variables and population size 30, with two different sets of values of (P_c, P_m) *viz.* (0.95, 0.02), (0.98, 0.01) and (0.99, 0.005) for 150 number of generations. SGSIM is used to interpolate the permeability of all the other grid blocks from the permeability values of these 40 pilot locations. Starting with the same initial population, fluid production rates are calculated by the simulator and objective function is evaluated. Objective function values of the initial ensembles for both the sets of (P_c, P_m) are given in Table 5.6. The minimum, maximum and mean objective function values were found to be 612.40, 2418.22 and 1357.13 respectively.

Table 5.6 Values of Objective function (Q) for 30 initial ensembles for Case (b)

Ensemble No.	Q	Ensemble No.	Q
1	1330.54	16	2012.51
2	1145.84	17	1355.03
3	1237.65	18	1436.19
4	999.19	19	943.45
5	1041.03	20	1886.42
6	1552.55	21	1799.45
7	2161.80	22	646.82
8	1499.65	23	1393.34
9	1493.53	24	726.58
10	2418.22	25	1426.20
11	1128.43	26	1814.36
12	612.40	27	1336.15
13	1247.54	28	714.83
14	1464.57	29	1169.28
15	1483.83	30	1242.09

The variation of ‘Q_{min}’ with generation is given in figure 5.6 below. The NSGA-II search was terminated after 150 generations that resulted in Q_{min} = 328.20, 334.55 and 329.89 for (P_c, P_m) = (0.95, 0.02), (0.98, 0.01) and (0.99, 0.005) respectively.

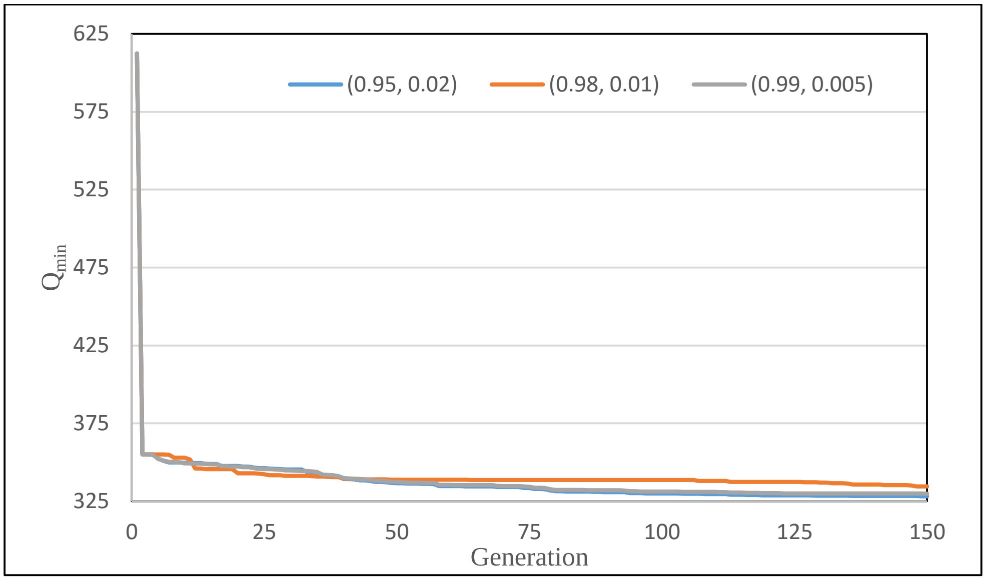


Figure 5.6: Variation of objective function ‘Q_{min}’ with generations for (P_c, P_m) = (0.95, 0.02), (0.98, 0.01) and (0.99, 0.005) for case (b)

5.2.3 Analysis of Results

In comparison to the case (a), Q_{min} started with a lower value (612.40 vs 1022.39). But, with every generation, the variation of Q_{min} was lower and finally it reached 328.20 (against 208.68 of case (a)). Hence, we can say that the reservoir model with permeability distribution obtained in case (a) with (P_c, P_m) = (0.95, 0.02) is a better one. However, parametric studies were carried out for the best case, by increasing and decreasing mutation/crossover probability keeping the other constant. The values of (P_c, P_m) chosen for the parametric studies are (0.95, 0.01), (0.95, 0.03), (0.94, 0.02) and (0.96, 0.02). The simulations were carried out and objective function ‘Q_{min}’ obtained were 220.22, 224.15, 219.38 and 211.65 respectively for the chosen (P_c, P_m). Of all the cases of (P_c, P_m) chosen, it is clear that the least value of objective function ‘Q_{min}’ was obtained for (P_c, P_m) = (0.95, 0.02), as evident from figure 5.7.

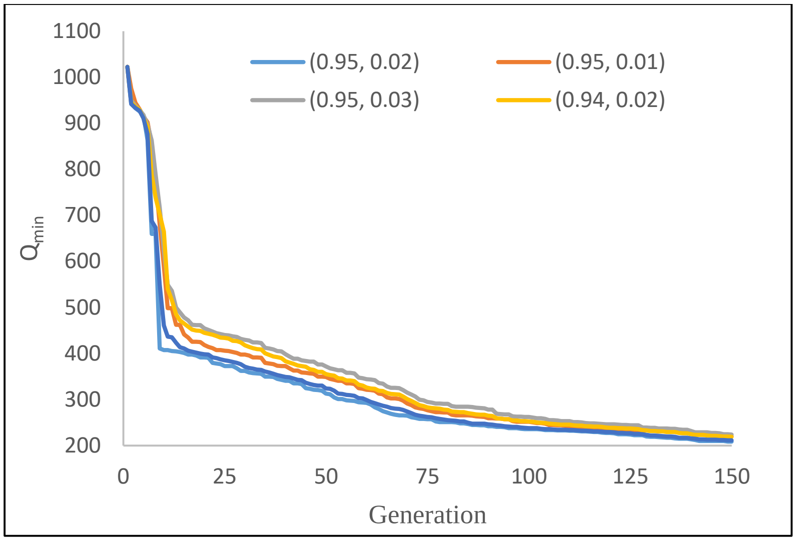
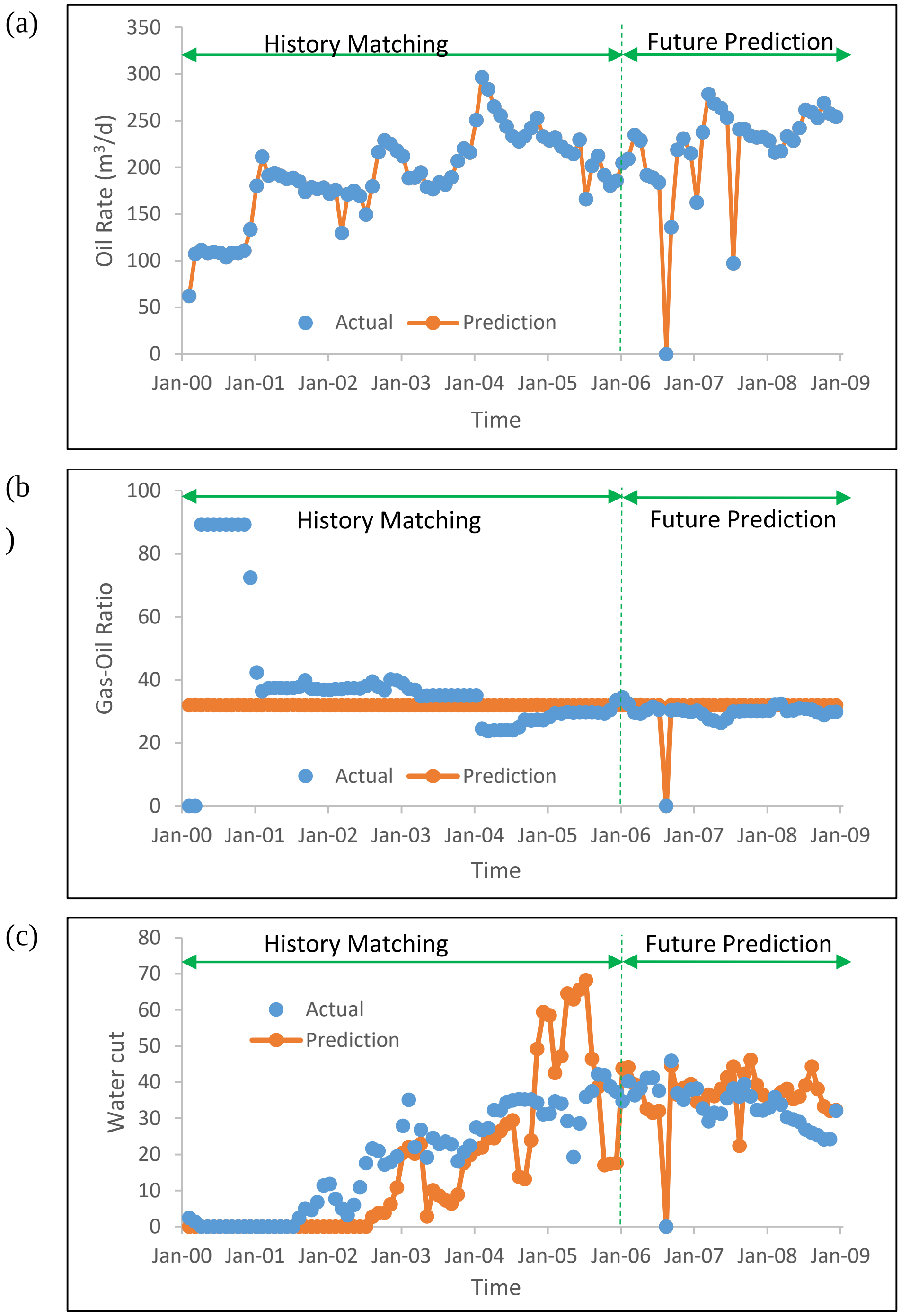


Figure 5.7: Parametric studies

Hence, the obtained permeability distribution was fed to the simulator for history matching and predict the reservoir performance. However, it may be noted that the higher values of gas-oil ratio (GOR) in the initial few months cannot be forecast from the developed model, the reasons of which were not well understood. This may be attributed to the possibility that the calculations of P-V-T properties might have got erred initially, which were corrected later. Mismatch in water cut during years 2003 and 2005 is also not clear enough and might be correlated to some event, which is unusual. Also, not so accurate water cut match may be attributed to the fact that two aquifers present maintains near constant reservoir pressure and provide strong water drive mechanism for reservoir production and there is no free gas cap. As mentioned earlier, finer course grid (say 10m x 10m) would have given much better results in terms of water cut with an increase in the complexity in GA calculations by 100 times and hence is not attempted. Also, in case (b), the number of pilot locations can significantly affect the value of objective function. Larger the number of pilot locations better may be the resultant permeability distribution and hence better reservoir model may be obtained. In general, it is not possible to match all the parameters for the considered time period owing to the structural complexities and non-homogeneities of actual reservoirs. The reservoir model with permeability distribution obtained in case (a) with $(P_c, P_m) = (0.95, 0.02)$ is used to predict the performance of the reservoir.



(d)

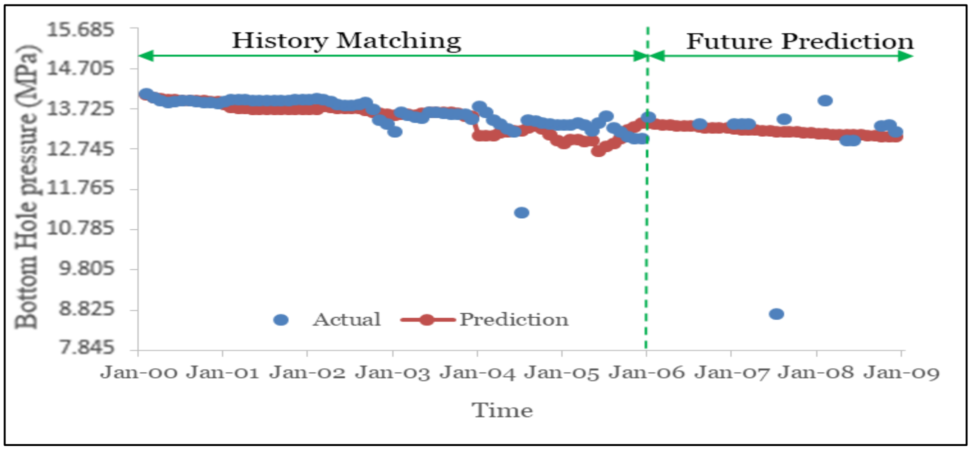
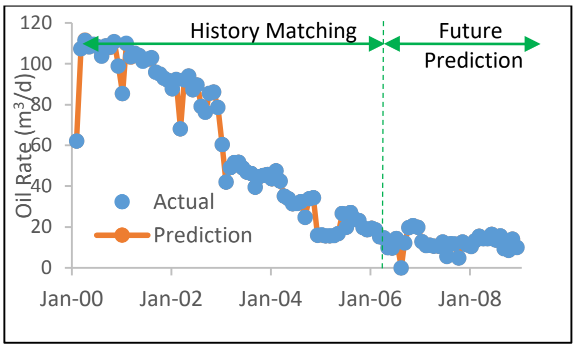
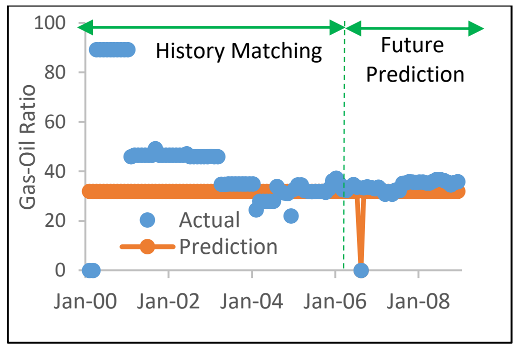


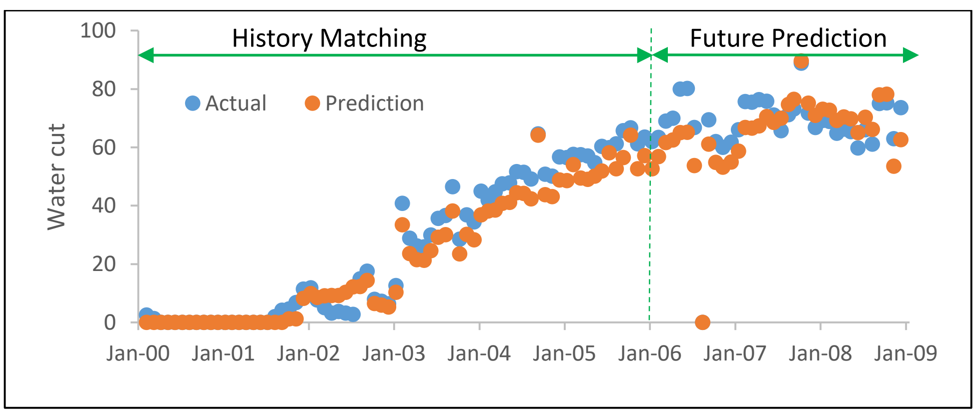
Figure 5.8: Comparison of predictions from the model with the field observations (a) Oil rate (b) GOR (c) Water cut and (d) BHP



Well-1. (a)

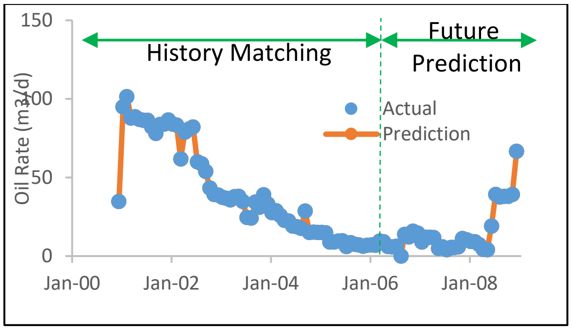


Well-1. (b)

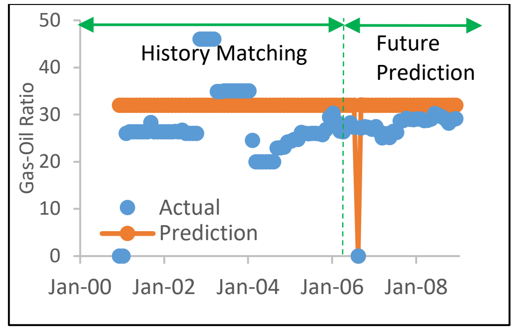


Well-1. (c)

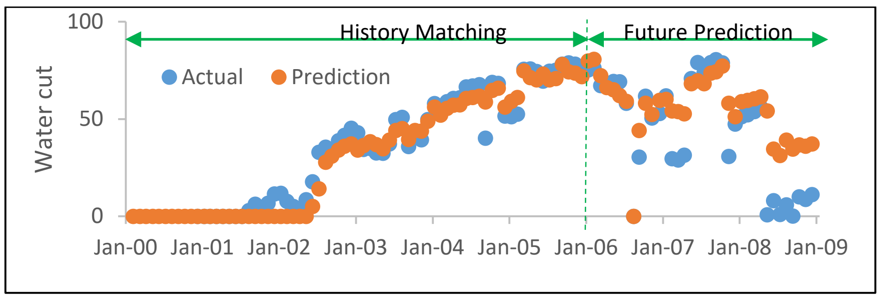
Figure 5.9 : Comparison of predictions from the model with the field observations for Well – 1 (a) Oil rate (b) GOR (c) Water cut



Well-2. (a)

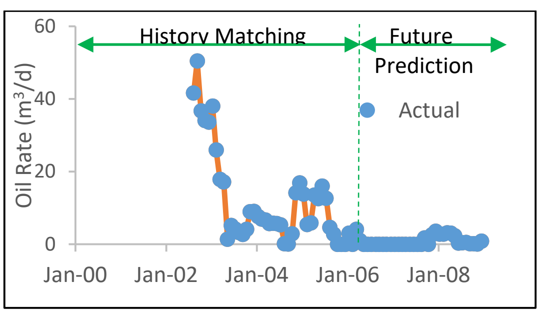


Well-2. (b)

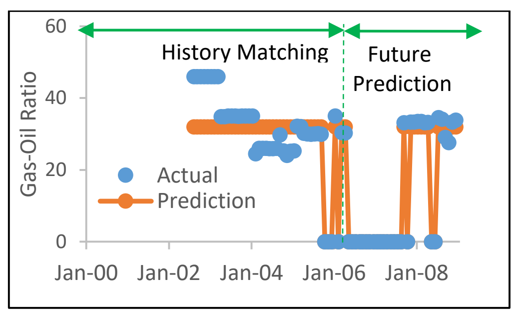


Well-2. (c)

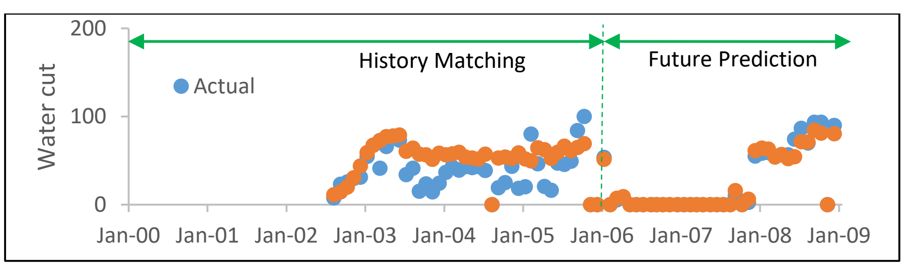
Figure 5.10: Comparison of predictions from the model with the field observations for Well – 2 (a) Oil rate (b) GOR (c) Water cut



Well-3. (a)

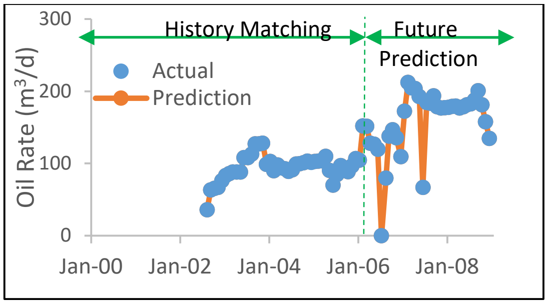


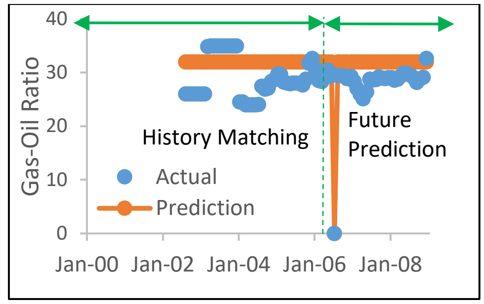
Well-3. (b)



Well-3. (c)

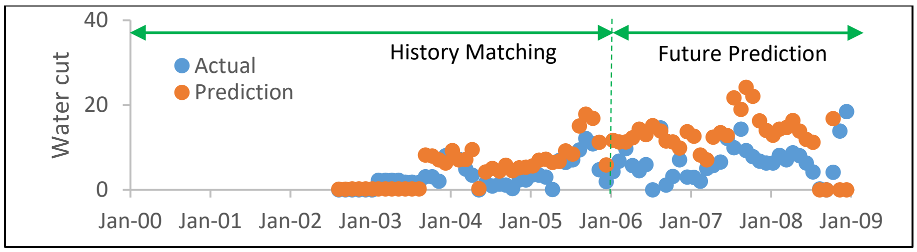
Figure 5.11: Comparison of predictions from the model with the field observations for Well – 3 (a) Oil rate (b) GOR (c) Water cut





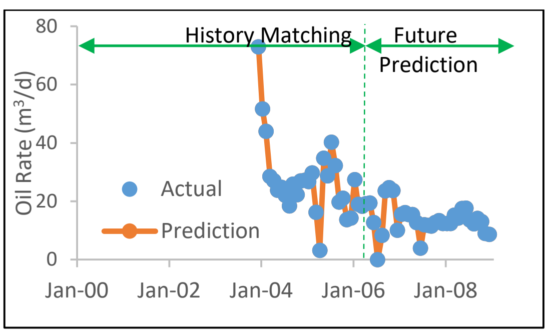
Well-4. (a)

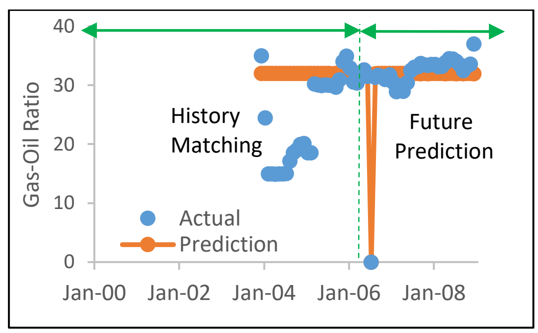
Well-4. (b)



Well-4. (c)

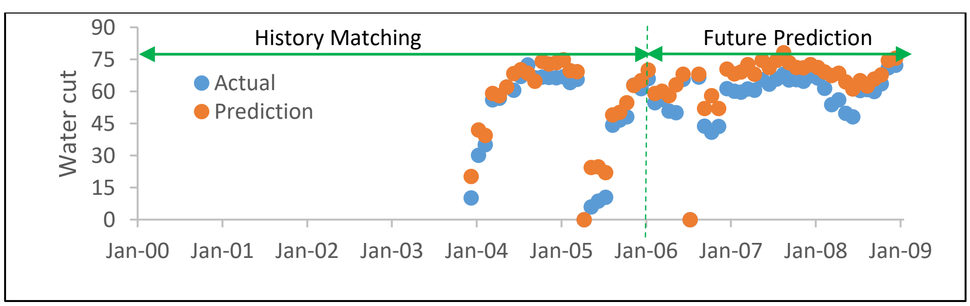
Figure 5.12: Comparison of predictions from the model with the field observations for Well – 4 (a) Oil rate (b) GOR (c) Water cut





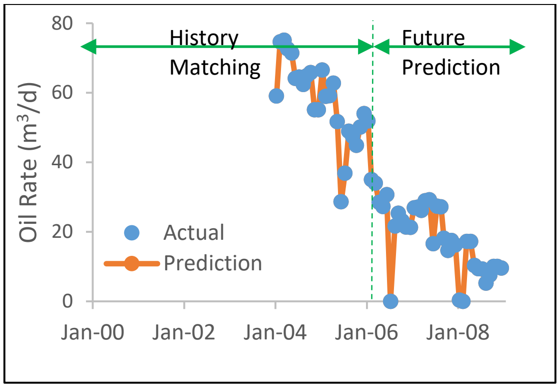
Well-5. (a)

Well-5. (b)

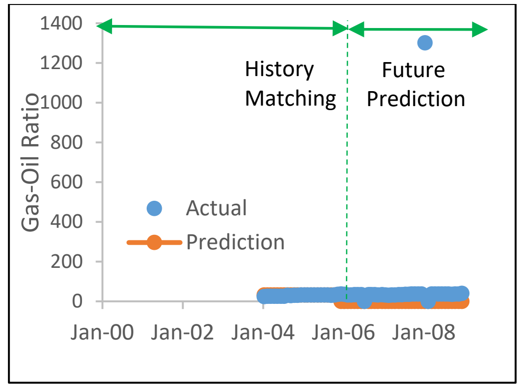


Well-5. (c)

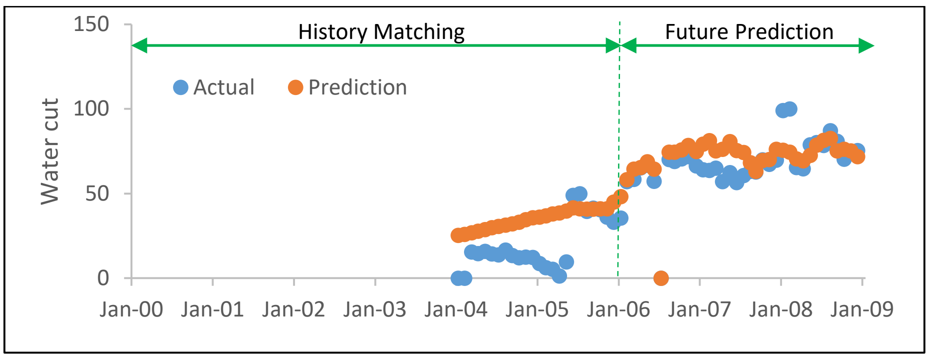
Figure 5.13: Comparison of predictions from the model with the field observations for Well – 5 (a) Oil rate (b) GOR (c) Water cut



Well-6. (a)



Well-6. (b)



Well-6. (c)

Figure 5.14: Comparison of predictions from the model with the field observations Well – 6 (a) Oil rate (b) GOR (c) Water cut

It is evident from the figure 5.8 (a) – (d) that the reservoir model generated predicts the reservoir performance to a good extent, though not accurate. Figures 5.9 – 5.14 show a match between production data and model predictions for individual wells for the time duration 2000 to 2008. The reservoir model is able to predict water cut, BHP and GOR well. The oil production rate continues to be matching exactly with the field observations. Thus, it can be affirmed that NSGA-II generated permeability distribution is indeed realistic and hence, the reservoir model developed is capable of future prediction.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

This chapter discusses the contribution from the present work, the extent of success achieved from the developed methodology for history matching and predicting the reservoir performance. A few recommendations for further research directions have also been included.

6.1 CONCLUSIONS

NSGA-II has shown its capability as a capable tool of optimization that assists in automated history matching, evident from its successful application in realizing a representative permeability map for 2-D synthetic reservoir. For the synthetic reservoir, results obtained by application of NSGA-II were in comparison with those results that were testified earlier by Chitralekha et al. (2010), using EnKF [103]. After validating the methodology, NSGA-II was applied to a real reservoir of grid block size 100 m × 100 m and history matching was performed. In first case, the number of variables was large, as each and every unknown permeability value, associated to a grid block, has been chosen as a variable. These variables were optimized using NSGA-II and objective function was evaluated.

In second case, the number of variables was reduced (keeping the grid block size same i.e.100 m × 100 m) by employing a network of pilot points along with SGSIM for non-linear interpolation. Permeability values at a set of pilot points, randomly spread throughout the reservoir, were chosen as variables. These variables were optimized using NSGA-II and the permeability values of neighboring grid blocks was calculated using SGSIM and objective function was evaluated. Though the values of objective function for both the cases are comparable, better fitness values were obtained with the technique NSGA-II, with better match for bottom hole pressure flowing pressure (BHP), gas-oil ratio (GOR), oil production rate and a reasonable match for watercut (WC). The mismatches could not be attributed to any specific reason, which might have occurred due to unusual events. The coarse grid size of 100m × 100 m may also have contributed to errors. Though the number of variables is reduced, run time of NSGA-II + SGSIM is found to be approximately 10% more than that of NSGA-II. This is due to the non-linear interpolation function being called upon every time, to generate the distribution map. However, the permeability distribution map that would have been obtained from NSGA-II + SGSIM, would be smooth and more realistic, as there shall be no abrupt increment/decrement in the permeability values of neighboring grid blocks. Nevertheless, abrupt increase/decrease in the values of permeability of neighboring grid blocks may be justified in this case, as the grid size chosen was coarse. Successful application of NSGA-II to obtain history matching of oil, gas and water and satisfactory future predictions establishes the efficiency of the technique to predict the reservoir performance and hence optimize the production.

6.2 RECOMMENDATIONS

- In this study, history matching using NSGA-II was attempted only with permeability. The methodology can be extended to include other critical parameter *viz.* porosity to enhance the efficiency of the history match.
- The present study is based on a simple 3-D black oil reservoir with 6 wells which could be extended to a complex reservoir with large number of wells.
- The coarse grid block size chosen in the current study may have introduced random error by improper accounting of spatial variations in rock properties. Accordingly, smaller grid block size can be chosen to get accurate model, with better configuration computers.
- In this study, history matching is based on a single objective that takes sum of square errors (SSE) of oil production rate, GOR, WC and BHP into consideration. Further studies can be carried out by multi-objective

matching which provide an increased diversity of matched model that results in improved forecasting.

- Reservoirs are heterogeneous and difficult to predict away from wells. Well data and seismic data have incomplete coverage and finite resolution and result in uncertainties. Further studies need developing reliable reservoir models handling these uncertainties.

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APPENDICES

APPENDIX – A: Source code of NSGA-II for history matching

Available with authors

APPENDIX – B: Data Used for Modeling of Real Reservoir

This section presents the relative permeability data used for real field modeling and the field historic data such as fluid production rate and bottom hole flowing pressure (BHP) used to compare the reservoir simulator response.

1. **Relative Permeability Data**

Layer 1			**Layer 2**			**Layer 3**		
Total Water Saturation (SWT)			**Total Water Saturation (SWT)**			**Total Water Saturation (SWT)**		
S_w	0.39		S_w	0.47		S_w	0.45	
S_{oirw}	0.24		S_{oirw}	0.21		S_{oirw}	0.22	
K_{ro}	0.984		K_{ro}	0.984		K_{ro}	0.984	
K_{rw}	0.084		K_{rw}	0.051		K_{rw}	0.061	
Total Liquid Saturation (SLT)			**Total Liquid Saturation (SLT)**			**Total Liquid Saturation (SLT)**		
S_{gc}	0.01		S_{gc}	0.03		S_{gc}	0.05	
K_{rog}	0.984		K_{rog}	0.984		K_{rog}	0.984	
K_{rg}	0.776	at $S_{wc}+S_{oir}$	K_{rg}	0.669	at $S_{wc}+S_{oir}$	K_{rg}	0.698	at $S_{wc}+S_{oir}$

2. Production history of the reservoir

Date (m/d/y)	Oil (m^3/day)	Gas (m^3/day)	Water (m^3/day)	Date (m/d/y)	Oil (m^3/day)	Gas (m^3/day)	Water (m^3/day)
3/1/2000	62.150	0.000	1.569	4/1/2003	188.965	6969.000	53.599
4/1/2000	107.442	0.000	1.468	5/1/2003	194.626	6789.000	71.417
5/1/2000	111.597	9966.933	0.000	6/1/2003	179.186	6260.742	42.571
6/1/2000	108.435	9684.742	0.000	7/1/2003	176.900	6191.500	57.617
7/1/2000	109.557	9782.033	0.000	8/1/2003	183.814	6433.484	54.574
8/1/2000	108.506	9690.065	0.000	9/1/2003	181.586	6355.484	55.933
9/1/2000	103.887	9275.935	0.000	10/1/2003	189.578	6635.133	56.066
10/1/2000	108.773	9711.833	0.000	11/1/2003	206.843	7239.548	45.651
11/1/2000	108.149	9655.903	0.000	12/1/2003	220.351	7712.533	57.203
12/1/2000	110.889	9899.400	0.000	1/1/2004	216.119	7564.323	62.541
1/1/2001	133.642	8830.903	0.000	2/1/2004	250.824	8778.871	95.204
2/1/2001	180.365	7628.903	0.000	3/1/2004	296.624	7267.276	108.429
3/1/2001	211.499	7699.857	0.000	4/1/2004	283.882	6728.677	106.816
4/1/2001	191.275	7146.516	0.000	5/1/2004	265.315	6359.967	126.685
5/1/2001	193.902	7250.767	0.000	6/1/2004	255.698	6132.484	121.604
6/1/2001	191.049	7153.516	0.000	7/1/2004	243.967	5879.233	128.468
7/1/2001	187.749	7008.733	0.000	8/1/2004	233.499	5603.968	125.461
8/1/2001	188.677	7053.613	0.000	9/1/2004	228.186	5702.032	124.525
9/1/2001	185.097	6973.935	4.636	10/1/2004	233.580	6381.667	126.972
10/1/2001	173.889	6933.100	9.297	11/1/2004	242.384	6589.968	131.526
11/1/2001	178.851	6646.355	8.706	12/1/2004	253.107	6915.033	132.418
12/1/2001	176.982	6556.400	12.841	1/1/2005	233.179	6344.097	105.199
1/1/2002	178.487	6572.581	23.011	2/1/2005	229.004	6467.097	104.345
2/1/2002	171.804	6312.742	23.059	3/1/2005	232.115	6820.250	123.619
3/1/2002	175.783	6511.821	14.648	4/1/2005	222.603	6505.290	115.333
4/1/2002	129.809	4806.065	6.850	5/1/2005	217.207	6471.300	90.015
5/1/2002	171.152	6387.833	5.598	6/1/2005	214.531	6342.839	51.242
6/1/2002	174.970	6525.484	11.307	7/1/2005	229.553	6812.200	91.841
7/1/2002	169.451	6316.633	20.667	8/1/2005	165.925	4919.581	93.168
8/1/2002	149.668	5685.323	31.936	9/1/2005	201.852	5990.935	120.797
9/1/2002	179.549	7082.774	49.655	10/1/2005	212.351	6285.233	154.727
10/1/2002	216.430	8163.567	57.440	11/1/2005	191.695	5615.452	138.519
11/1/2002	229.096	8401.839	47.586	12/1/2005	180.717	5498.933	114.775
12/1/2002	225.021	9037.600	49.013	1/1/2006	185.979	6230.581	110.793
1/1/2003	217.920	8687.323	52.512	2/1/2006	204.586	7043.968	108.780
2/1/2003	212.094	8240.194	82.270	3/1/2006	209.230	6782.321	140.979
3/1/2003	188.402	6996.464	102.113	4/1/2006	234.786	6933.290	134.350

Date (m/d/y)	Oil (m3/day)	Gas (m3/day)	Water (m3/day)	Date (m/d/y)	Oil (m3/day)	Gas (m3/day)	Water (m3/day)
5/1/2006	228.956	6711.367	142.127	10/1/2007	241.322	7280.033	157.591
6/1/2006	191.814	5838.323	134.106	11/1/2007	233.869	7057.161	131.802
7/1/2006	189.097	5947.500	132.649	12/1/2007	232.301	7008.533	110.749
8/1/2006	184.060	5621.806	110.957	1/1/2008	232.835	7018.484	110.377
9/1/2006	0.000	0.000	0.000	2/1/2008	228.755	6920.194	112.445
10/1/2006	135.952	4126.067	115.480	3/1/2008	215.960	6947.172	120.806
11/1/2006	218.896	6670.161	128.454	4/1/2008	217.335	7030.613	110.861
12/1/2006	230.890	6989.067	124.959	5/1/2008	233.520	7033.433	101.516
1/1/2007	215.210	6410.452	131.966	6/1/2008	228.715	6943.226	96.645
2/1/2007	162.644	4923.677	100.823	7/1/2008	242.173	7516.133	98.878
3/1/2007	237.711	6913.250	115.706	8/1/2008	261.729	8069.484	96.208
4/1/2007	278.696	7684.387	114.911	9/1/2008	259.152	7905.290	91.054
5/1/2007	268.754	7282.333	123.534	10/1/2008	252.880	7506.833	85.908
6/1/2007	263.666	6938.742	119.886	11/1/2008	269.159	7752.161	85.669
7/1/2007	253.401	7027.767	139.545	12/1/2008	257.732	7665.133	82.308
8/1/2007	97.228	2908.000	60.218	1/1/2009	254.287	7600.097	120.242
9/1/2007	240.976	7242.032	135.956				

Pressure field History of Reservoir

Date	BHP (kg/cm^2)	Date	BHP (kg/cm^2)	Date	BHP (kg/cm^2)
21/2/2000	143.87	31/12/2003	138.61	21/12/2005	132.53
29/5/2000	141.66	6/1/2004	137.56	16/2/2006	138.05
3/8/2000	142.04	4/2/2004	140.55	21/9/2006	136.37
11/1/2001	141.3	16/4/2004	137.13	22/2/2007	136.27
8/3/2001	142.28	5/7/2004	134.41	28/3/2007	136.17
27/9/2001	142.0	6/8/2004	114.19	30/7/2007	88.97
6/3/2002	142.48	2/9/2004	137.12	14/8/2007	137.45
17/8/2002	140.77	2/10/2004	138.23	20/3/2008	142.12
19/9/2002	140.96	17/1/2005	136.06	24/5/2008	132.09
9/10/2002	141.58	17/3/2005	136.08	18/6/2008	132.2
19/12/2002	137.30	18/5/2005	136.08	19/11/2008	135.76
21/2/2003	134.29	2/6/2005	134.66	10/12/2008	136.1
13/3/2003	139.19	19/7/2005	136.58		
2/6/2003	137.69	23/8/2005	138.23		
18/7/2003	139.11	15/9/2005	135.18		

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