APPLICATION OF EVOLUTIONARY ALGORITHM FOR ASSISTED HISTORY MATCHING

by

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CERTIFICATION OF APPROVAL

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Approved by,

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CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

MUHAMMAD IZZAT BIN ZAHARI

ABSTRACT

History matching is a fundamental technique in reservoir engineering principle. Successful reservoir interpretation mostly depends on the precision of the history matching. History matching is an act of adjusting the developed model in simulating the past reservoir performance to match the actual historical data. From the outcome, engineers are able to estimate the future production rate of the well closely based on parameters like pressure, relative permeability and porosity. When the differences between the observed performance data and simulated data are found, the iterations are made to modify the accuracy of the match. Traditionally, this iterative technique is computed manually which is very time consuming.

The development of history matching technique has evolved rapidly over the past 20 years from manual to automated history matching. As the technology moving on, history matching is also improvised in scope of optimization. Generally, history matching consists of manual and automatic computation. Manual execution commonly apply trial-and-error concept which the probability ranges is quite uncertain and time consuming. Besides, it really demands skill and experience on the part of simulation engineer. Today, tremendous efforts are made to develop Automatic History Matching algorithms. While the automatic method focus on optimization which is normally computer based.

In this project, we will define and discuss the application of evolutionary algorithm in assisted history matching. Evolutionary method helps to find the global minima directly without the presence of local minima. Besides, algorithm based method has been widely used to forecast future result in various field for example art, biology, marketing including engineering. The methodology will be tested on developed synthetic model.

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In this opportunity, I would like to credit my supervisor, Berihun Mamo Negash for giving his tremendous support to me to accomplish my final year project. It is not an easy task at first as the project is not favourable for me as the project is reservoir studies related. However, I manage to adapt the case study with his crucial help. Upon completion of this project, I gain more knowledge on reservoir simulation and it is very beneficial to me. Besides, I also have improved my skill in using simulation software especially ECLIPSE which is used as part of project execution. Generally, this software have been used widely as fundamental in subsurface evaluation and exploration and production (E&P). I believe it will be very useful that can be practised in my future undertaking. Definitely it is good addition to my skill and knowledge.

Special thanks to my group member which are doing History Matching project together that shares what it takes to finish the project. With everyone assistance in the group, I am able to enhance and modify my methodology till I can achieve the satisfied result. Thanks also to my friends from Reservoir Engineering major that help me indirectly to learn more about reservoir simulation.

Last but not least, I want to thanks UTP and my sponsor Majlis Amanah Rakyat (MARA) for funding my thesis. I hope that my project, *Application of Evolutionary Algorithm for Assisted History Matching* will be continued by the students after me to give innovative idea that can bring this project one step ahead and contribute to the Oil & Gas industry.

TABLE OF CONTENTS

CERTIFICATION	i
ABSTRACT	iii
ACKNOWLEDGEMENT	iv

CHAPTER 1: INTRODUCTION

1.1	Background of Study	1
1.2	Problem Statement	2
1.3	Objective	3
1.4	Scope of Study	3

CHAPTER 2: THEORY

2.1	The Forward Model	5
2.2	The Objective Function	12
2.3	Optimization by Evolutionary Algorithm	13

CHAPTER 3: LITERATURE REVIEW

3.1	Optimization by Genetic Algorithm	14
3.2	Genetic Algorithm Approach in Other Field	
	Application	16

CHAPTER 4: METHODOLOGY

4.1	Research methodology	17
4.2	Tools	26

CHAPTER 5: RESULTS & DISCUSSION

5.1	Data Gathering	27
5.2	Discussion	31

REFERENCES	34
APPENDICES	35

LIST OF FIGURES

Figure 1: Structure of a single population Evolutionary Algorithm	2
Figure 2: Synthetic model	18
Figure 3: Process of optimization by Genetic Algorithm	24
Figure 4: Oil saturation when the water injection starts	27
Figure 5: Oil saturation at the end of production	28
Figure 6: Field oil production total vs. Time	28
Figure 7: Field oil production rate vs. Time	29
Figure 8: Production vs Time curve	30
Figure 9: Interface of Genetic Algorithm in Optimization Tool MATLAB	31
Figure 10: The Fitness value and Average Distance vs. Generation curve	
of the objective function	31
Figure 11: History Matched curve of Field Oil Production Total	32
Figure 12: History Matched curve of Oil Production Rate	32

LIST OF TABLES

Table 1: Grid location of the wells.	17
Table 2: Well parameter	18
Table 3: Permeability of the set of simulation	19

CHAPTER 1: INTRODUCTION

1.1 Background

History Matching consists of three stages of computation. It starts with developing Forward model, secondly by applying objective function and lastly the history matching will be completed by optimization technique. The efficiency of the history matching of uncertain reservoir is very crucial in several of reservoir engineering application such as development optimization. Application of optimization is always become a major focus to reservoir engineering. Nowadays, optimization algorithm is used for assisted history matching by computers through numerous of advanced software. While many applications that is used to assist history matching such as genetic algorithms, differential evolution, particle swarm optimization and ensemble Kalman filter (EnKF), evolutionary algorithm is a promising technique for better history match result. However, evolutionary is an interesting method as it has tendency to avoid local minima but, it is identified to slow down the convergence simulation. Generally, Evolutionary algorithms (EAs) are a group of optimization encouraged by biological evolution.

It works on a population of possible solutions by applying the principle of survival to the fittest to generate promising approximations to a solution. Throughout the selection process, the fittest individuals will create the new approximation and expanding those using operators from natural genetics. Then, the process will eventually will form the evolution of populations of individuals that are adapted to their environment than the individuals that they were created from, just as in natural adaptation.

Besides selection, recombination, mutation, the other examples of evolutionary algorithms model natural processes, are, migration, locality and neighbourhood. Evolutionary algorithms work on populations of individuals instead of single solutions. In this way the search is performed in a parallel manner. **FIGURE 1** shows the structure of a simple evolutionary algorithm.



FIGURE 1: Structure of a single population Evolutionary Algorithm

1.2 Problem Statement

The problem with time consuming to compute the result of manual history matching has become a major problem. As the result, the feasibility of this technique used for a single deterministic model has become questionable which later will affect the fiscal costs -[1]. Moreover, manual history matching is not openly demonstrated. In addition, this technique really requires the intelligence and skill of the expert to perform history matching manually. The lack of experiences of using history matching tools and error application without consider the engineering judgement may lead the user to several potential pitfalls which are unrealistic -[2]

The optimization technique has been widely developed. Gradient techniques are the one tool that pioneering the optimization. These particular techniques have great efficiency in terms of convergence between simulation data and observed data. However, they always has problem with local minima of the objective function which will yield premature convergence of the search algorithm -[1]

Therefore, in this study, evolutionary algorithm application will be optimized to the fullest to assist history matching to achieve better result in a short time. Some of evolutionary algorithm will be applied to search for the global parameter search space in the conceptual model. The adaptation method is used to amend the search quality.

1.3 Objective

General Objective

To reduce computational time of history matching through application of evolutionary algorithm

Specific objective

- To develop the synthetic model
- Selecting the most outstanding method of Evolutionary Algorithm

1.4 Scope of Study

During the project time frame, the research will emphasis on developing the synthetic reservoir model to run a simulation and apply history matching technique Then, history matching process will be started with forward model, objective function and end up with evolutionary algorithm application as optimization purpose.



This scope of study will be conducted during Final Year Project I & Final Year Project II. Below are the details :-

1.4.1 Final Year Project I

- Research and detail study regarding the History Matching and Evolutionary Algorithm optimization method
- Developing the Forward model from material balance and diffusivity equation

1.4.2 Final Year Project II

- Compute Objective Function
- Illustrate a synthetic model for reservoir data obtained from undisclosed field in Peninsular Malaysia using Eclipse software
- Comparing the Evolutionary Algorithm to choose the best for history matching

CHAPTER 2: THEORY

History matching is the fundamental technique in aiding reservoir engineering simulation. In the end, the future production performance can be predicted based on the results of history matching. The parameters involved includes pressure, water oil ratio (WOR), gas oil ratio (GOR), water gas ratio (WGR), water and gas arrival times, fluid saturation from cores, well logs, chemical tracer test, seismic time travel, time-lapse seismic amplitude and time-lapse AVO gradient and intercepts -[3]

2.1 Forward Model

This kind of model is developed based on the fundamental physical laws and specified by certain parameters to simulate the behaviour of actual reservoir system. A typical forward problem is shown by a differential equation with specified initial/or boundary conditions. For example, the relating forward problem that is the following steady-state problem from a one-dimensional in a porous medium:

$$\frac{d}{dx}\left(\frac{k(x)A}{\mu}\frac{dp(x)}{dx}\right) = 0$$

For 0 < x < L, and

$$\frac{dp}{dx}\Big|_{x=L} = -\frac{q\mu}{k(L)A}$$

 $p(0) = p_e$

Where A (cross sectional area to flow in cm²), μ (viscosity in cp), q (flow rate in cm³/s), L (length) and pressure p_e atm are assumed to be constant. The function k(x) represents the permeability field in Darcies. [3] stated in their paper that the

mathematical model (forward model) required for the estimation of unknown parameters in this research consists of reservoir simulator (ECLIPSE) to model the flow of fluid through porous media and rock physic model (petro-elastic and forward seismic model) to compute seismic responses.

2.1.1 Conservation of Mass

The transient flow is considered in the model which means accumulation of fluid (water/gas) occurs in the flow. The equation below includes time dependency through the right hand side term.

$$\frac{\partial^2 P}{\partial x^2} = \left(\frac{\phi \mu c}{k}\right) \frac{\partial P}{\partial t}$$



{Mass into the element at x} - {Mass out the element x + Dx} = {Rate of change of mass inside the element}

$$\{\mu\rho A\}_x - \{\mu\rho A\}_{x+\Delta x}$$

Dividing above equation by Δx ,

$$-\frac{\partial}{\partial x}(A\rho u) \pm q = A\frac{\partial}{\partial t}(\phi\rho)$$

Considering one dimension with multiphase (oil and water) flow in the reservoir :-

$$-\frac{\partial}{\partial x}(\rho_{l}u_{l}) \pm q = \frac{\partial}{\partial t}(\phi\rho_{l}S_{l}), \quad l = o, w.g$$

where the corresponding Darcy's equation for each phase:-

$$u_{l} = -\frac{kk_{rl}}{\mu_{l}}\frac{\partial P_{l}}{\partial x}, \quad l = o, w, g$$

One phase of Oil

$$\rho_o = \frac{\rho_{oS} + \rho_{gS} R_{so}}{B_o}$$

For undersaturated oil, R_{so} is constant. Therefore the equation can be written as:-

$$\rho_o = \frac{constant}{B_o}$$

One phase of Water

$$\rho_w = \frac{\rho_{ws}}{B_w} = \frac{constant}{B_w}$$

By substituting Darcy equation and density, ρ into the flow equation gives :-

$$\frac{\partial}{\partial x} \left(\frac{kk_{ro}}{\mu_o B_o} \frac{\partial P_o}{\partial x} \right) = \frac{\partial}{\partial t} \left(\frac{\phi S_o}{B_o} \right) - OIL$$

$$\frac{\partial}{\partial x} \left(\frac{kk_{rw}}{\mu_w B_w} \frac{\partial P_w}{\partial x} \right) = \frac{\partial}{\partial t} \left(\frac{\phi S_w}{B_w} \right) - WATER$$

where

$$P_w = P_o - P_{cow}$$
$$S_o + S_w = 1$$

2.1.2 Discretization of flow equations

<u>Left side</u>

The oil transmissibility term $,T_{xo}:$

$$T_{xoi+\frac{1}{2}} = \frac{2\lambda_{oi+\frac{1}{2}}}{\Delta x_i \left[\frac{\Delta x_{i+1}}{k_{i+1}} + \frac{\Delta x_i}{k_i}\right]} \qquad \qquad T_{xoi-\frac{1}{2}} = \frac{2\lambda_{oi-\frac{1}{2}}}{\Delta x_i \left[\frac{\Delta x_{i-1}}{k_{i-1}} + \frac{\Delta x_i}{k_i}\right]}$$

The oil mobility term, λ_o is defined as

$$\lambda_o = \frac{k_{ro}}{\mu_o B_o}$$

By rearranging the flow equation in term of T_{xo} and λ_o gives :-

$$\frac{\partial}{\partial x} \left(\frac{kk_{ro}}{\mu_o B_o} \frac{\partial P_o}{\partial x} \right) \approx T_{xoi + \frac{1}{2}} (P_{oi+1} - P_{oi}) + T_{xoi - \frac{1}{2}} (P_{oi-1} - P_{oi}) - OIL$$

$$\frac{\partial}{\partial x} \left(\frac{kk_{rw}}{\mu_w B_w} \frac{\partial P_w}{\partial x} \right) \approx T_{xwi + \frac{1}{2}} (P_{wi+1} - P_{wi}) + T_{xwi - \frac{1}{2}} (P_{wi-1} - P_{wi}) - WATER$$

Upstream selection of mobility

$$\lambda_{oi+\frac{1}{2}}f(x) = \begin{cases} \lambda_{oi+1} & \text{if } P_{oi+1} \ge P_{oi} \\ \lambda_{oi} & \text{if } P_{oi+1} \le P_{oi} \end{cases} - OIL$$
$$\lambda_{oi+\frac{1}{2}}f(x) = \begin{cases} \lambda_{wi+1} & \text{if } P_{wi+1} \ge P_{wi} \\ \lambda_{wi} & \text{if } P_{wi+1} \le P_{wi} \end{cases} - WATER$$

<u>Right side</u>

By using the Chain Rule,

OIL

$$\frac{\partial}{\partial t} \left[\frac{\phi S_o}{B_o} \right] = \frac{\phi}{B_o} \frac{\partial S_o}{\partial t} + S_o \frac{\partial}{\partial t} \left[\frac{\phi}{B_o} \right]$$

For the second term

$$\frac{\partial}{\partial t} \left[\frac{\phi}{B_o} \right] \approx \frac{\phi_i}{\Delta t} \left[\frac{c_r}{B_o} + \frac{d(1/B_o)}{dP_o} \right] (P_o - P_{oi}^t)$$

For the first term, we replace oil saturation by water saturation:-

$$\frac{\partial S_w}{\partial t} = -\frac{\partial S_o}{\partial t}$$

By using standard backward approximation of time derivative,

$$\left[\frac{\phi}{B_o}\frac{\partial S_o}{\partial t}\right] = \frac{\phi_i}{B_o\Delta t_i}(S_{wi} - S_{wi}^t)$$

where,

$$C_{pooi} = \phi_i \frac{(1 - S_{wi})}{\Delta t} \left[\frac{C_r}{B_o} + \frac{d(\frac{1}{B})}{dP_o} \right]$$
$$C_{swoi} = -\frac{\phi_i}{B_{oi}\Delta t_i}$$

Substituting C_{pooi} and C_{swoi} into flow equation,

$$\frac{\partial}{\partial t} \left[\frac{\phi S_o}{B_o} \right] \approx C_{pooi} (P_{oi} - P_{oi}^t) + C_{swoi} (S_{wi} - S_{wi}^t)$$

WATER

$$\frac{\partial}{\partial t} \left[\frac{\phi S_w}{B_w} \right] = \frac{\phi}{B_w} \frac{\partial S_w}{\partial t} + S_w \frac{\partial}{\partial t} \left[\frac{\phi}{B_w} \right]$$

For the second term,

$$\frac{\partial}{\partial t} \left[\frac{\phi}{B_w} \right] = \frac{\partial}{\partial P_o} \left[\frac{\phi}{B_w} \right] \frac{\partial P_w}{\partial t}$$
$$= \frac{\partial}{\partial P_w} \left[\frac{\phi}{B_w} \right] \left[\frac{\partial P_o}{\partial t} \right]$$

For the first term, capillary pressure is a function of water saturation

$$\frac{\partial P_{cow}}{\partial} = \frac{\partial P_{cow}}{\partial S_w} \frac{\partial S_w}{\partial t}$$

where

$$C_{powi} = \frac{\phi S_{wi}}{\Delta t} \left[\frac{C_r}{B_o} + \frac{d(\frac{1}{B})}{dP_w} \right]$$
$$C_{swwi} = -\frac{\phi_i}{B_{oi}\Delta t_i} - \left[\frac{\partial P_{cow}}{\partial S_w} \right] C_{powi}$$

Substituting C_{powi} and C_{powi} into the flow equation,

$$\frac{\partial}{\partial t} \left[\frac{\phi S_w}{B_w} \right] = C_{powi} (P_{oi} - P_{oi}^t) + C_{swwi} (S_{wi} - S_{wi}^t)$$

The discrete forms can be written as

$$T_{xoi+\frac{1}{2}}(P_{oi+1} - P_{oi}^{t}) + T_{xoi-\frac{1}{2}}(P_{oi-1} - P_{oi}^{t}) - q'_{oi} - OIL$$

= $C_{pooi}(P_{oi} - P_{oi}^{t}) + S_{woi}(S_{wi} - S_{wi}^{t})$

$$T_{xwi+\frac{1}{2}}[(P_{oi+1} - P_{oi}^{t}) - (P_{cowi+1} - P_{cow})] + T_{xwi-\frac{1}{2}}[(P_{oi-1} - P_{oi}^{t}) - (P_{cowi-1} - P_{cow})] - q'_{wi} = C_{powi}(P_{oi} - P_{oi}^{t}) + S_{wwi}(S_{wi} - S_{wi}^{t}) - WATER$$

2.1.3 Solution by IMPES method

$$T_{xo}^{t}, T_{xw}^{t}$$

$$C_{po}^{t}, C_{pw}^{t}$$

$$C_{so}^{t}, C_{sw}^{t}$$

$$P_{cow}^{t}$$

$$T_{xoi+\frac{1}{2}}(P_{oi+1} - P_{oi}^{t}) + T_{xoi-\frac{1}{2}}(P_{oi-1} - P_{oi}^{t}) - q'_{oi}$$

= $C_{pooi}(P_{oi} - P_{oi}^{t}) + S_{woi}(S_{wi} - S_{wi}^{t})$ $i = I, N$

$$T_{xwi+\frac{1}{2}}[(P_{oi+1} - P_{oi}^{t}) - (P_{cowi+1} - P_{cow})] + T_{xwi-\frac{1}{2}}[(P_{oi-1} - P_{oi}^{t}) - (P_{cowi-1} - P_{cow})] - q'_{wi} = C_{powi}(P_{oi} - P_{oi}^{t}) + S_{wwi}(S_{wi} - S_{wi}^{t}) \qquad i = I, N$$

IMPES Pressure Solution

$$\alpha_i = -\frac{C_{swwi}^t}{C_{swoi}^t}$$

Substitute into flow equation,

$$\begin{pmatrix} T_{xoi+\frac{1}{2}}^{t} + \alpha_{i}T_{xwi+\frac{1}{2}}^{t} \end{pmatrix} (P_{oi+1} + P_{oi}) + \begin{pmatrix} T_{xoi-\frac{1}{2}}^{t} + \alpha_{i}T_{xwi-\frac{1}{2}}^{t} \end{pmatrix} (P_{oi-1} + P_{oi}) - \alpha_{i}T_{xwi+\frac{1}{2}}^{t} (P_{cowi+1} - P_{cowi})^{t} - \alpha_{i}T_{xwi-\frac{1}{2}}^{t} (P_{cowi-1} - P_{cowi})^{t} - q_{oi}' - \alpha_{i}q_{wi}' = (C_{pooi}^{t} + \alpha_{i}C_{pwoi}^{t})(P_{oi} - P_{oi}^{t}) \qquad i = I.N$$

Rearranging the term according to group,

$$a_i = T_{xoi-\frac{1}{2}}^t + \alpha_i T_{xwi-\frac{1}{2}}^t$$

$$c_{i} = T_{xoi+\frac{1}{2}}^{t} + \alpha_{i}T_{xwi+\frac{1}{2}}^{t}$$

$$b_{i} = -\left(T_{xoi+\frac{1}{2}}^{t} + T_{xoi-\frac{1}{2}}^{t} + C_{pooi}^{t}\right) - \alpha_{i}\left(T_{xwi+\frac{1}{2}}^{t} + T_{xwi-\frac{1}{2}}^{t} + C_{pwoi}^{t}\right)$$

$$d_{i} = -(C_{pooi}^{t} + \alpha_{i}C_{pwoi}^{t})P_{oi}^{t} + q_{oi}' - \alpha_{i}q_{wi}' + \alpha_{i}T_{xwi+\frac{1}{2}}^{t}(P_{cowi+1} - P_{cowi})^{t}$$
$$\alpha_{i}T_{xwi-\frac{1}{2}}^{t}(P_{cowi-1} - P_{cowi})^{t}$$

Therefore the pressure equation can be written as,

$$a_i P_{oi-1} + b_i P_{oi+1} + c_i P_{oi+1} = d_i$$
 $i = I, N$

2.1.4 Modifications for Boundary Conditions

For production of oil and water with specified bottomhole pressure

$$q'_{oi} = \frac{WC_i}{A\Delta x_i} \lambda_{oi} (P_{oi} - P_{bhi})$$
$$q'_{wi} = \frac{WC_i}{A\Delta x_i} \lambda_{wi} (P_{wi} - P_{bhi})$$

where

Well Constant, WC =
$$\frac{2\pi k_i h}{\ln\left(\frac{re}{rw}\right)}$$

 $Drainage \ radius, r_e = \frac{2\pi\kappa_i h}{\ln\left(\frac{re}{rw}\right)}$

Thus, the following matrix coefficients are modified :

$$\begin{split} b_i &= -\left(T_{xoi+\frac{1}{2}}^t + T_{xoi-\frac{1}{2}}^t + C_{pooi}^t\right) \\ &\quad -\alpha_i \left(T_{xwi+\frac{1}{2}}^t + T_{xwi-\frac{1}{2}}^t + C_{pwoi}^t + \frac{WC_i}{A\Delta x_i} \left[\frac{B_{oi}}{B_{wi}}\lambda_{oi} + \lambda_{wi}^t\right]\right) \\ d_i &= -\left(C_{pooi}^t + \alpha_i C_{pwoi}^t\right) P_{oi}^t - \frac{WC_i}{A\Delta x_i} \lambda_{oi}^t P_{bhi} - q_{oi}' - \alpha_i \frac{WC_i}{A\Delta x_i} \left[\frac{B_{oi}}{B_{wi}}\lambda_{oi} + \lambda_{wi}^t\right] P_{bhi} \\ &\quad \alpha_i T_{xwi+\frac{1}{2}}^t (P_{cowi+1} - P_{cowi})^t + \alpha_i T_{xwi-\frac{1}{2}}^t (P_{cowi-1} - P_{cowi})^t \end{split}$$

2.2 The Objective Function

The objective function can be defined as the amount of inconsistency between the historical data such as seismic survey, production history data, pressure and the simulator response for a given parameter. It is similar like to calculate the error between the observed and simulated data. According to - [3], there are three common formulas in calculating objective function :-

-Least-Square Formulation

$$\mathbf{F} = \left(d^{obs} - d^{cal}\right)^T \left(d^{obs} - d^{cal}\right)$$

-Weighted Least-Square Formulation

$$\mathbf{F} = \left(d^{obs} - d^{cal}\right)^T w \left(d^{obs} - d^{cal}\right)$$

-Generalized Least-Square Formulation

$$F = \frac{1}{2}(1-\beta)\left\{ \left(d^{obs} - d^{cal}\right)C_d^{-1}\left(d^{obs} - d^{cal}\right)\right\} + \frac{1}{2}\beta\left\{ \left(\alpha - \alpha_{prior}\right)^T C_\alpha^{-1}\left(\alpha - \alpha_{prior}\right)\right\}$$

Where d^{obs} represents the observed data, d^{cal} the response of the system, w is a diagonal matrix, β is a weighting factor, C_d is covariance matrix of the data and C_{α} is the covariance matrix of the parameters of the mathematical model. In history matching, objective function can be divided into local components and seismic zone. Local components is usually referred to the well depends on the smaller number of parameter. The partial separability of objective function can assist in resolve derivatives in smaller number of the simulation for gradient based optimization technique -[4]. There are several researches done to study the effect of objective

function in history matching. According to-[5] the work on objective function used in history matching must be particular due to its influence on the optimization performance method. Their research shows that the square error global objective function obtained smaller number of simulation which is the most highlighted function. Meanwhile, the simple error objective function yields a good result but has slow convergence. Several studies related to fluid flow in the reservoir have also help to improve the objective function. From the evaluations, suitable approach requires the acceptance of an objective function will have to partner up lag time with deviation-based statistics in order to improve history matching -[6]. As a result, faster convergence and less computational time are obtained. However, using the least square objective function can results term that are difficult to reduced. Some of the alternative developed by -[7] is generated from image analysis tool to improve the formulation. According to- [7] by using an alternative formulation as a comparison for several images with different injection scenarios to a reference case shows this formulation is more steady to calculate the difference between images instead of least square formulation.

2.3 Evolutionary Algorithm

An evolutionary algorithm is optimization method that is inspired from biological evolution of living thing such as offspring. It operates based on the principle of survival to the fittest. The most common algorithm in evolutionary algorithm is genetic algorithm and evolutionary strategies. In genetic algorithm, decision variable are initialized as an individual called chromosome. The population is evolves by genetic algorithm by the process of selection, recombination and mutation. The process will be looped until it finds the best fit of the solution. When the evolution stops, the individual with the best fitness indicates the optimal solution of the optimization case.

CHAPTER 3: LITERATURE REVIEW

3.1 Optimization by Genetic Algorithm

Historically, several methods that have been used in optimizing history matching result. According to -[8], the gradient technique is effective to build convergence between the simulation and the production data but somehow it is easily stranded in local minima of the objective function. As a result, the premature convergence will be obtained of the search algorithm. The computation of numerical derivatives also requires evaluation of the objective function which are very expensive -[4]. Evolutionary Algorithm is proven to be better formula as it can avoid the local minima that will need further solution and time consuming.

Genetic algorithm is identified as the most used evolutionary algorithm in optimization process. As stated earlier, evolutionary algorithm inspired from biological evolution. Commonly, genetic algorithm is the distinction of the list of parameter by using binary code scheme that transforms in an analog of the chromosome -[8]. The usual steps in genetic algorithm are selection, mutation, crossover and coding. [9] stated that eventhough evolutionary methods such as Covariance Matrix Adaptation – Evolution Strategy (CMAES) or genetic algorithm are fit for well modelling, their efficiency is relied on various parameters involved in the model. Genetic Algorithm have been shown to have broad range of application includes nuclear reactor management, gas pipeline operation, process control and aircraft design -[10]. The main advantage of genetic algorithm is its tendency to converge towards the model with great fitness values for rational crossover and mutation distribution of probability-[8] That's the reason why genetic algorithm can be succeed in complex function in optimization.

Another successful evolutionary algorithm is evolution strategies that usually used for continuous parameter optimization. While, genetic algorithm uses probabilistic selection, evolution strategies select deterministic approach. The research by done by -[8] found that evolutionary algorithm seems to has better optimization problem of history match due to high non-linearities in reservoir parameter to be improved. Linearities function will be able to solve easily rather than non-linearities function. Key advantage of this method is the simple translation of model parameters into the language of coded optimization parameters used by the optimization module -[11]

Stochastic evolutionary algorithm is also considered to be one of the common methods in history matching. The particle swarm optimization is a stochastic evolutionary algorithm which is inspired in social behaviour of individuals in nature such as bird flocking and fish schooling -[12]. Like other evolutionary algorithm, stochastic algorithm is quite simple to implement due to its ability to find the global convergence. The problem in this algorithm includes computational demands and trouble in parameter tuning. For this case, an adaptation method in adjusting control parameter of evolutionary algorithm can be suggested to improve the search quality. Based on -[13], the comparison of original evolutionary algorithm and adaptive evolutionary algorithm shown that adaptive evolutionary algorithm is able to find the range of fitting models with better convergence with minimum misfit.

However, different evolutionary algorithm will react contrarily in terms of level of diversity. Therefore, population-based evolutionary algorithm (PBEA) should be measured to ensure the history-matched results of the algorithm in control and good quality. Algorithms with less number of reservoir simulation is very crucial and demanding to assist history matching as the objective function computation is costly. Diversity measures are defined and design based on the concepts of exploration and exploitation -[13].

Evolutionary algorithms are commonly applied in classic single objective optimization. It means that all the objective parameters equivalent to the well measurements are totalled into a single objective. As the nature of history matching is multi-objective, the multiple objective optimization become an immediate alternative. This is because it has ability to separately improve the multi-objective corresponding to the different qualities to be matched -[8]. Pareto-based multi objective evolutionary algorithm (MOEA) is the one that able to find the set of optimal named Pareto optimal. Based on -[14], Pareto-based multi objective evolutionary algorithm (MOEA) outperforms the commonly used aggregation-based genetic algorithm (GA-SOP) in history matching application.

3.2 Genetic Algorithm Approach in Other Field Application

As the most frequent evolutionary algorithm, genetic algorithm has been successful in solving various problems. For example, the problem in soft drink production requires a lot of sizing and scheduling decisions should be produced at the same time for raw material preparation/storage in tanks and soft drink bottling in several production lines minimizing inventory, shortage and setup costs. The objective is similar to history matching which is to reduce the time computation as well minimize the cost. According to - [15] the hardest part in the problem is reduced by this method once the genetic algorithm and mathematical programming (GAMP) provides binary information (sequences), which can deal with simple and fast continuous linear model for lot sizes. It is stated that GAMP is more suitable to evaluate real-world problem instances than pure mathematical programming methods.

Another field like transportation also implements genetic algorithm to solve the problem encountered. For example, transit network design problem is sensitive in finding of a set of routes with corresponding schedules for a public transport system. -[16] conduct a research on designing the transit network while giving a preference to maximize the number of satisfied passengers and to minimize the total travel time. Using genetic algorithm with elitism (GAWE), they find it is competitive with other approaches as it can generate high quality solutions within the sensible CPU times. Based on the example above, genetic algorithm will become more effective optimization tool when it is combined with other appropriate method.

CHAPTER 4: METHODOLOGY

4.1 Research Methodology

4.1.1 Synthetic Model Development

A synthetic model is developed by altering some properties from the original Odeh Field. Initially, Odeh field has 2 well which is producer and injector well. For this project, another 3 gas injector well have been added to the field to optimise the production rate and the total production. This method is made to generate data for historical and simulated data. **TABLE 1** and **TABLE 2** below show the general descriptions of the well:-

Dimension

10 X 10 X 3

Well/Location	i	j	k1	k2
Producer	5	5	3	3
Injector 1	1	1	3	3
Injector 2	10	1	3	3
Injector 3	1	10	3	3
Injector 4	10	10	3	3

Size(ft)	DX : 300 X 1000
	DY : 300 X 1000
	DZ: 100 X 20(first layer)
	100 X 30(second layer)
	100 X 50(third layer)
Porosity,¢	0.3
Viscosity,µ(cp)	0.31
Oil Formation Volume Factor, B _o	1.726
Bottom hole Pressure,BHP(psia)	4800
Fluid present	Oil,water,gas and dissolved gas

 TABLE 2 : Well parameter



FIGURE 2 : Synthetic model

4.1.2 Sensitivity Analysis

This method is used to provide a data that are relevant to solve during optimization phase. Besides it is to validate the data that we guess for simulation. In this synthetic model, several permeabilities have been added to check the effect towards the model. Then sensitivity analysis has to be made to select the observed and simulated data for optimization. Here, permeability value will be changed to yield different production curve. Each permeability will give different simulation result. The production will be simulated for 1216 days. From the results obtained the graph will be plotted. Below are the permeabilities tested for each set of injection:-

Set/Attempt	Permeability range /k
GAS_INJECTION	1-499
GAS_INJECTION1	500-999
GAS_INJECTION2	1000-1499
GAS_INJECTION3	1500-1999
GAS_INJECTION4	2000 -3000

TABLE 3 : Permeability of the set of simulation

4.1.3 Solving the Objective Function

Objective Function will calculate the error between the simulated data and historical data. It will calculate based on Least square method:-

 $OF = (Function of Q_{historical} - Function of Q_{simulated})^2$

Historical permeability

PERM 1 (500mD)	PERM 2 (970mD)		PERM 1 (550mD)	PERM 2 (590mD)	PERM 1 (800mD)	PERM 2 (850mD)
PERM 3 (640mD)	PERM 4 (750mD)		PERM 3 (600mD)	PERM 4 (700mD)	PERM 3 (680mD)	PERM 4 (700mD)
Тор			Mide	dle	Botto	m



PERM 1	PERM 2	PERM 1	PERM 2	PERM 1	PERM 2
(2700mD)	(2250mD)	(2150mD)	(2400mD)	(2050mD)	(2600mD)
PERM 3	PERM 4	PERM 3	PERM 4	PERM 3	PERM 4
(2300mD)	(2900mD)	(2550mD)	(2690mD)	(2500mD)	(1850mD)
Toj	р	Middle		Bottom	

The permeability above is the tested data that is going to use to solve the unknown which is the real permeability that match to the historical permeability. The other parameter like bottomhole pressure, area, width, viscosity, porosity and oil formation volume factor are kept constant.

The finite-difference equations for all grid points may now be written in a matrix form as :-

 $TP^{n+1} = D(P^{n+1} - P^n) + G + Q$ $= D\Delta_l P + G + Q$

where

 \mathbf{T} = transmissibility matrix,

 \mathbf{D} = accumulation matrix,

 \mathbf{G} = vector of gravity of gravity terms(assumed to be expressed explicitly at the time level *n*)

For model 10 x 10 x 3, the accumulation in this field are coming from block $Producer_{(5,5)}$, Injector1 (1,1), Injector2(10,1), Injector3(1,10) and Injector4(10,10) in the bottom layer

$$d_{1,1} = \frac{v}{\Delta t} [(\phi S_g)^n b'_g - (\phi b_g)^{n+1} S'_g + \frac{1}{2} b_g^{n+1} S_g^n \phi']$$

= $\frac{666.67}{30} [(0.3)(0) - (0.3)(0.2485)(166.666) + \frac{1}{2}((12.093)(0.2485)(0.3)]$
= -266.0943

$$\begin{aligned} d_{10,1} &= \frac{v}{\Delta t} [(\phi b_g)^{n+1} S'_g + \frac{1}{2} b_g^{n+1} S_g^n \phi'] \\ &= \frac{666.67}{30} [(0.3)(0)(166.666) + \frac{1}{2}((12.093)0.2543)(0.3)] \\ &= 0.7698 \end{aligned}$$

$$d_{5,5} = \frac{V}{\Delta t} [(\phi b_o)^{n+1} S'_o + \frac{1}{2} b_o^{n+1} S_o^n \phi']$$

= $\frac{666.67}{30} [(0.3)(0.88)(0.18) + \frac{1}{2}(0.87)(0.28)(0.3)]$
= 1.8680

$$d_{1,10} = \frac{V}{\Delta t} [(\phi b_g)^{n+1} S'_g + \frac{1}{2} b_g^{n+1} (1 - S_g^n) \phi']$$

= $\frac{666.67}{30} [(0.3)(0)(166.666) + \frac{1}{2}(12.093)(1-0.2323)(0.3)]$
= 39.5404

$$d_{10,10} = \frac{v}{\Delta t} \Big[(\phi(1 - S_g))^n b'_g - (\phi b_g)^{n+1} S'_g + \frac{1}{2} b_g^{n+1} (1 - S_g^n) \phi' \Big]$$

= $\frac{666.67}{30} [((0.3)(1)(166.666) - (0.3)(166.666) + \frac{1}{2}(12.093)(1 - 0.2385)(0.3)]$
= 30.6962

$$\lambda_{o} = \frac{k_{ro}}{\mu_{o}B_{o}}$$

$$= \frac{0.7}{(1.04)(1.062)}$$

$$= 0.6338$$

$$T_{i+\frac{1}{2}} = \lambda_{i+\frac{1}{2}} \left(\frac{A_{i+\frac{1}{2}}}{\Delta x_{i+\frac{1}{2}}}\right)$$

$$= 0.6338 \left(\frac{100}{10}\right)$$

$$= 6.338$$

*The values above are obtained from the synthetic data

The partitons of **G** and **Q** :-

$$\mathbf{G}_{\mathbf{i}} = \begin{bmatrix} \Delta T_{o1} \gamma_{o1} \Delta z \\ \Delta T_{o2} \gamma_{o2} \Delta z \\ \Delta T_{o3} \gamma_{o3} \Delta z \\ \Delta T_{o3} \gamma_{o3} \Delta z \\ \Delta T_{o5} \gamma_{o5} \Delta z \\ \Delta T_{o5} \gamma_{o5} \Delta z \\ \Delta T_{o7} \gamma_{o7} \Delta z \\ \Delta T_{o9} \gamma_{o9} \Delta z \\ \Delta T_{o10} \gamma_{o10} \Delta z \end{bmatrix} \quad \mathbf{Q}_{\mathbf{i}} = \begin{bmatrix} Q_{o1} \\ Q_{o2} \\ Q_{o3} \\ Q_{o3} \\ Q_{o4} \\ Q_{o5} \\ Q_{o6} \\ Q_{o7} \\ Q_{o8} \\ Q_{o9} \\ Q_{o10} \end{bmatrix}$$

The equation above can be written as :-

$$\begin{bmatrix} T_{1,1}T_{1,2}T_{1,3}T_{1,4}T_{1,5}T_{1,6}T_{1,7}T_{1,8}T_{1,9} & T_{1,10} \\ T_{2,1}T_{2,2}T_{2,3}T_{2,4}T_{2,5}T_{2,6}T_{2,7}T_{2,8} & T_{2,9} & T_{2,10} \\ T_{3,1}T_{3,2}T_{3,3}T_{3,4}T_{3,5}T_{3,6}T_{3,7} & T_{3,8} & T_{3,9} & T_{3,10} \\ T_{4,1}T_{4,2}T_{4,3}T_{4,4}T_{4,5}T_{4,6} & T_{4,7} & T_{4,8} & T_{4,9} & T_{4,10} \\ T_{5,1}T_{5,2}T_{5,3}T_{5,4}T_{5,5} & T_{5,6} & T_{5,7} & T_{5,8} & T_{5,9} & T_{5,10} \\ T_{6,1}T_{6,2}T_{6,3}T_{6,4} & T_{6,5} & T_{6,6} & T_{6,7} & T_{6,8} & T_{6,9} & T_{6,10} \\ T_{7,1}T_{7,2}T_{7,3} & T_{7,4} & T_{7,5} & T_{7,6} & T_{7,7} & T_{7,8} & T_{7,9} & T_{7,10} \\ T_{8,1}T_{8,2} & T_{8,3} & T_{8,4} & T_{8,5} & T_{8,6} & T_{8,7} & T_{8,8} & T_{8,9} & T_{8,10} \\ T_{9,1} & T_{9,2} & T_{9,3} & T_{9,4} & T_{9,5} & T_{9,6} & T_{9,7} & T_{9,8} & T_{9,9} & T_{9,10} \\ T_{10,1} & T_{10,2} & T_{10,3} & T_{10,4} & T_{10,5} & T_{10,6} & T_{10,7} & T_{10,8} & T_{10,9} & T_{10,10} \end{bmatrix}$$

$[P_{o1}]$	n+1		$\Delta_t P_1$		G_{o1}		Q_{o1}	L
P_{o2}			$\Delta_t P_2$		G_{o2}		Q_{o2}	
P_{o3}		г d1 1 1	$\Delta_t P_3$		G_{o3}		Q_{o3}	
P_{o4}		$d_{1,1}$	$\Delta_t P_4$		G_{o4}		Q_{o4}	
P_{o5}	_	$d_{10,1}$	$\Delta_t P_5$		G_{o5}		Q_{o5}	
P_{o6}	_	u _{5,5}	$\Delta_t P_6$	+	G_{o6}	+	Q_{o6}	
P_{o7}		$u_{10,1}$	$\Delta_t P_7$		G_{o7}		Q_{o7}	
P_{o8}		$[a_{10,10}]$	$\Delta_t P_8$		G_{o8}		Q_{o8}	
<i>P</i> ₀₉			$\Delta_t P_9$		G_{o9}		Q_{o9}	
$[P_{o10}]$			$\Delta_t P_{10}$		$[G_{o10}]$		Q_{o10}	

4.1.3 Evolutionary Algorithm Application Using Genetic Algorithm

Genetic Algorithm is the class of evolutionary algorithm that commonly used. Basically, genetic algorithm applies selection, recombination and mutation to find its possible solution for the unknown parameters. Furthermore, genetic algorithm does not require parameters reduction step such as Principal Component Analysis (PCA) and Discrete Cosine Transformation (DCT). Evolutionary algorithm which is basically the stochastic and population based algorithm will be utilized to solve the history matching problem. This method will be implemented by computational software which is MATLAB to reduce the misfit data between historical and simulated data.



FIGURE 3 : Process of optimization by Genetic Algorithm

Below is the process of Genetic Algorithm:-

Step 1: Initialization

The number of chromosomes, generation are determined along with and mutation rate and crossover rate value

Step 2: Evaluation

Then, the chromosome number of population is generated, and initial value of the genes chromosome-chromosome are assumed with a randomly. The fitness value of chromosomes is computed by defining objective function, f(x) where

$$f(x) = ((a + 2b + 3c + 4d))$$

Step 3: Selection

The fittest individuals will have the higher probability to be picked up for the next process. In order to compute probability value, the fitness of the individual/chromosome must be computed first. The value of 1 is added to avoid dividing by 0.

$$Fitness[1] = 1 / (1 + F_obj[1])$$

Then the probability for each chromosomes is formulated by:

Step 4: Crossover

In this stage, two chromosomes are randomly selected from the duplicated population. Then they will be recombined to produce two new offsprings. There are several ways to crossover two new chromosomes. One method is called single-point crossover, in both chromosomes swap their bits at a randomly selected position with a probability. Another one is known as uniform crossover where the two chromosomes will exchange their bits at every position based on probability.

The pseudo-code for the crossover process is as follows:-

 $k \leftarrow 0$; while(k<population) do $R[k] \leftarrow random (0-1)$; if ($R[k] < \rho c$) then select Chromosome[k] as parent; end; k = k + 1; end; end;

Step 5: Mutation

The method is to increase diversity of the population. Mutation process is done by replacing the gen at random position with a new value. Total length of gen is:-

total_gen= number_of_gen_in_Chromosome * number of population

Step 6. New Chromosomes (Offspring)

* Steps 3-6 will be looped until the number of generations is produced

Step 7. Solution (Best Chromosomes)

These new Chromosomes will undergo the same process as the previous generation of Chromosomes such as evaluation, selection, crossover and mutation and at the end it produce new generation of chromosome for the next iteration. This iteration process will be repeated until a set number of generations

4.2 Tools

- Eclipse 2009 Reservoir Simulation software
- Microsoft Excel 2010
- MATLAB software

CHAPTER 5: RESULT AND DISCUSSION

5.1 Data Gathering

5.1.1 Flow Model Simulation

The model is simulated in Floviz to see the presence of hydrocarbon fluid and its movement in the field throughout the production period. Four injectors well are located at the edge of the field while the producer is at the middle. All injector well are flowing at the same rate at 25 000 STBD.



FIGURE 4: Oil saturation when the water injection starts

From the **FIGURE 4** above, it shows that the oil is mostly saturated in three layers, while the water breakthrough only at top layer as the injection is started in all four well. When this happens, oil is accumulated through producer at the center of the field model. Oil saturation starts to increase in the block around the producing block. It shows that the model is functional as the oil is flowing up in the field. Therefore the reservoir model is validated.



FIGURE 5: Oil saturation at the end of production

At the end of the production, the intensity of water is higher than the oil produced. **FIGURE 5** above shows top layer has been fully occupied by water. The producer will produce only water at this time.

5.1.2 Sensitivity Analysis

Sensitivity analysis is constructed by combining all the curve to give the clear variation of the permeabilities to the original case. In this case, GAS_INJECTION is the original case. The graphs below are obtained from Office in Eclipse.



FIGURE 6: Field oil production total vs. Time

Based on the graph above, GAS_INJECTION3 which has the highest permeability range scores the same oil rate with GAS_INJECTION1. Its mean the permeability changes higher than permeability of GAS_INJECTION1 do not give any significant increase anymore.



FIGURE 7: Field oil production rate vs. Time

Field oil production shows all the curves are decreased significantly except for the base case, GAS_INJECTION which gives slight elevation throughout the production period. Due to different results given, it can be said that the model is validated as it can detect the changes in permeability thus gives different production data.



5.1.3 Historical Data vs. Simulated Data

FIGURE 8: Production vs. Time curve

The graph above shows Field Production Oil Rate and Field Oil Production Total. The red lines which is injection1 is selected as historical data while the blue lines from injection4 are representing the simulated data. From the graph, there is difference or gap between the historical lines and simulated lines.

The result above is expected to be continued for next stage which is Objective Function and Optimization using Genetic Algorithm which is one of the Evolutionary Algorithm. The objective function will then calculate the discrepancy of the production history and simulation data while optimization will regress the simulated curve as close as possible to observed or historical curve.

5.2 Discussion

The result of the history matching is obtained after genetic algorithm is applied towards the objective function. It is known that genetic algorithm works based on the probabilistic principle as the result obtained is different for each simulation even it is constantly initialized. Therefore, the result is choosen based on the least iteration number for each simulation run. The best fit for each individual or unknown is achieved after 53 iterations run.

File Help							
Problem Setup and Results	Options						
Solver: ga - Genetic Algorithm	Fitness limit: • Use default: -Inf						
Problem	C Specify:						
Fitness function: @objective	Stall generations: Use default: 50						
Number of variables: 12	C Specify:						
Constraints:	Stall time limit: 🕫 Use default: Inf						
Linear inequalities: A: b:	C Specify:						
Linear equalities: Aeq: beq:	Function tolerance:						
Bounds: Lower: Upper: Upper:	C Specify:						
Nonlinear constraint function:	Nonlinear constraint tolerance: Use default: 1e-6						
Run solver and view results	C Specific						
☐ Use random states from previous run	Plot functions						
Start Pause Stop	Plot interval: 1						
Current iteration: 53 Clear Results	Best fitness Est individual F Distance						
Optimization running.	Expectation Genealogy Range						
Objective function value: 1.193131638234485E9 Optimization terminated: average change in the fitness value less than options.TolFun.	☐ Score diversity ☐ Scores ☐ Selection						
	□ Stopping □ Max constraint						
3	Custom function:						
Final point:	Output function						
1 2 3 4 5 6 7 8 9 10 11 12 4.409 -12.539 6.574 7.378 5.496 -18.11 4.285 4.475 4.02 3.639 -5.334 -1.69	Custom function:						

FIGURE 9: Interface of Genetic Algorithm in Optimization Tool MATLAB



FIGURE 10: The Fitness value and Average Distance vs. Generation curve of the objective function

The 12 unknown permeabilities data are minimized to its best fit towards the historical data. From the **FIGURE 11** and **FIGURE 12** below, the newly history matched curve are constructed for graph field production total and oil production rate. Both data are starts to be matched at the time where both historical and simulated data divert from each other. It also records less than 5 seconds to match the historical data. The total oil production and reservoir pressure graph shows that genetic algorithms tested high volume of the search space that avoid the local minima. However, their convergence is quite slow to reach the global optimum.



FIGURE 11: History Matched curve of Field Oil Production Total



FIGURE 12: History Matched curve of Oil Production Rate

CHAPTER 6: CONCLUSION & RECOMMENDATION

History matching is the most vital tools in simulating reservoir to forecast the future performance especially in brown field reservoir. The process is like trial and error which modifies unknown reservoir parameters to improve the gap, calculated in an objective function (in this case is permeability and reservoir pressure). Evolutionary algorithm is proven to be the reliable optimization algorithm as it tendency to avoid the local minima and high non-linearities. Thus, it does not require parameter reduction like any other optimization does yet it has saved the time. Besides, evolutionary algorithm has been widely used in other field in solving problem regarding unknown parameters which enable the forecast prediction.

For future recommendation, multi-objective optimization techniques can be applied to enhance the result of the algorithm. This is described as multi-objective objective intends to solve multiple optima and is more successful as respect to single objective optimization. At the end this project achieved the objective which is to reduce the computational time of history matching thus boost the reservoir simulation interpretation.

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APPENDIX I

Eclipse Model for base case

👕 Peto_injection1 - Notepad
File Edit Format View Help
THIS IS THE FIRST SPE COMPARISON PROBLEM, "COMPARISON OF SOLUTIONS TO A THREE-DIMENSIONAL BLACK-OIL RESERVOIR SIMULATION PROBLEM", REPORTED BY AZIS AND ODEH AT THE SPE SYMPOSIUM ON RESERVOIR SIMULATION , JANUARY 1981. IT IS A NON SWELLING AND SWELLING STUDY. A REGULAR GRID WITH TWO WELLS (INJECTOR AND PRODUCER)AND A IMPES SOLUTION METHOD IS USED FOR THIS SIMULATION. THE PRODUCTION IS CONTROLLED BY FLOW RATE AND MIN. BHP. OIL RATE, GOR, PRESSURE AND GAS SATURATION ARE TO BE REPORTED. BUINSPEC
TITLE ODEH PROBLEM - IMPLICIT OPTION - 1200 DAYS
DIMENS
10 10 3 / NONNC
OIL
WATER
GAS
DISGAS
1 100 50 1 50 /
TABDIMS 1 1 16 12 1 12 /
WELLDIMS 5 16 5 2 /
NUPCOL 4 /
START 19 'OCT' 1982 /
NSTACK 24 /
FMTOUT
UNIFIN
NOSIM
GRID
ROCK PERMEABILITIES AND POROSITIES ARE DEFINED.
THE X AND Y DIRECTION CELL SIZES (DX, DY) AND THE PORDSTILES ARE CONSTANT THROUGHOUT THE GRID. THESE ARE SET IN THE FIRST 3 LINES AFTER THE EQUALS KEYWORD. THE CELL THICKNESSES (DZ) AND PERMEABILITES ARE THEN SET FOR EACH LAYER. THE CELL TOP DEPTHS (TOPS) ARE NEEDED ONLY IN THE TOP LAYER (THOUGH THEY COULD BE. SET THROUGHOUT THE GRID). THE SPECIFIED MULTZ VALUES ACT AS MULTIPLIERS ON THE TRANSMISSIBILITIES BETWEEN THE CURRENT LAYER AND THE LAYER BELOW.
INIT ARRAY VALUE BOX
'DX' 1000 /
'DY' 1000 / 'PORO' 0.3 /
First Layer 'DZ' 20 1 5 1 5 1 1 / 'PERMX' 500 / 'MULTZ' 0.64 / 'TOPS' 8325 /
'DZ' 20 6 10 1 5 1 1 / 'PERMX' 970 / 'MULTZ' 0.64 / 'TOPS' 8325 /
'DZ' 20 1 5 6 10 1 1 / 'PERMX' 640 / 'MULTZ' 0.64 / 'TOPS' 8325 /
'DZ' 20 6 10 6 10 1 1 / 'PERMX' 750 / 'MULTZ' 0.64 / 'TOPS' 8325 /
second Layer
'DZ' 30 1 5 1 5 2 2 / 'PERMX' 550 / 'MULTZ' 0.265625 /

. 'DZ' 30 'PERMX' 590 / 'MULTZ' 0.265625 / 6 10 1 5 2 2 / 'DZ' 30 'PERMX' 600 / 'MULTZ' 0.265625 / 1 5 6 10 2 2 / 'DZ' 30 'PERMX' 700 / 'MULTZ' 0.265625 / 6 10 6 10 2 2 / -Third Layer 'DZ' 50 'PERMX' 800 151533/ 'DZ' 50 'PERMX' 850 6 10 1 5 3 3 / 1 1561033/ 'DZ' 50 'PERMX' 680 'DZ' 50 'PERMX' 700 6 10 6 10 3 3 / EQUALS IS TERMINATED BY A NULL RECORD THE Y AND Z DIRECTION PERMEABILITIES ARE COPIED FROM PERMX SOURCE DESTINATION ------ BOX -----COPY 'PERMX' 'PERMY' 1 10 1 10 1 3 / 'PERMX' 'PERMZ' / / -- OUTPUT OF DX, DY, DZ, PERMX, PERMY, PERMZ, MULTZ, PORO AND TOPS DATA -- IS REQUESTED, AND OF THE CALCULATED PORE VOLUMES AND X, Y AND Z -- TRANSMISSIBILITIES RPTGRID 1 1 1 1 1 1 0 0 1 1 0 1 1 0 1 1 / - WATER RELATIVE PERMEABILITY AND CAPILLARY PRESSURE ARE TABULATED AS - A FUNCTION OF WATER SATURATION. -- SWAT KRW PCOW SWFN_ 0.12 0 0 1.0 0.00001 0 / - SIMILARLY FOR GAS -- SGAS KRG SGFN 0 0 0.02 0 0.05 0.005 0.12 0.025 0.2 0.075 0.25 0.125 0.3 0.19 0.4 0.41 0.45 0.6 0.5 0.72 0.6 0.87 0.7 0.94 0.85 0.98 1.0 1.0 SGAS KRG PCOG OIL RELATIVE PERMEABILITY IS TABULATED AGAINST OIL SATURATION FOR OIL-WATER AND OIL-GAS-CONNATE WATER CASES ____ SOIL KROW KROG 50F 3 0 0 0.0001 0.001 0.021 0.09 0.2 0.35 0.7 0.98 0.997 1 1 0 0.0001 0.001 0.021 0.09 0.2 0.35 0.7 0.98 0.997 1 0 0.18 0.28 0.38 0.43 0.48 0.58 0.63 0.63 0.76 0.83 0.86 0.86 0.879 0.88 1 1 - PVT PROPERTIES OF WATER -- REF. PRES. REF. FVF COMPRESSIBILITY REF VISCOSITY VISCOSIBILITY PVTW 4014.7 1.029 3.13D-6 0.31 0 / - ROCK COMPRESSIBILITY -- REF. PRES COMPRESSIBILITY 14.7 3.0D-6

-- SURFACE DENSITIES OF RESERVOIR FLUIDS --- OIL WATER GAS 49.1 64.79 0.06054 / - PVT PROPERTIES OF DRY GAS (NO VAPOURISED OIL) - WE WOULD USE PVTG TO SPECIFY THE PROPERTIES OF WET GAS PGAS BGAS VISGAS
 Mail
 Mail
 Mail
 Mail

 14.7
 166.666
 0.008

 264.7
 12.093
 0.0096

 514.7
 6.274
 0.0112

 1014.7
 3.197
 0.014

 2014.7
 1.614
 0.0208

 3014.7
 1.294
 0.0208

 3014.7
 0.811
 0.0268

 5014.7
 0.649
 0.0309

 9014.7
 0.386
 0.047
 PVDG PVT PROPERTIES OF LIVE OIL (WITH DISSOLVED GAS) WE WOULD USE PVDO TO SPECIFY THE PROPERTIES OF DEAD OIL FOR EACH VALUE OF RS THE SATURATION PRESSURE, FVF AND VISCOSITY ARE SPECIFIED. FOR RS=1.27 AND 1.618, THE FVF AND VISCOSITY OF UNDERSATURATED OIL ARE DEFINED AS A FUNCTION OF PRESSURE. DATA FOR UNDERSATURATED OIL MAY BE SUPPLIED FOR ANY RS, BUT MUST BE SUPPLIED FOR THE HIGHEST RS (1.618). RS POIL FVFO VISO PVTO $\begin{array}{c} 1.04\\ 0.975\\ 0.91\\ 0.83\\ 0.695\\ 0.641\\ 0.594\\ 0.51\\ 0.549\\ 0.74\\ 0.449\\ 0.605\end{array}$ / - OUTPUT CONTROLS FOR PROPS DATA - ACTIVATED FOR SOF3, SWFN, SGFN, PVTW, PVDG, DENSITY AND ROCK KEYWORDS RPTPROPS 1 1 1 0 1 1 1 1 / -- DATA FOR INITIALISING FLUIDS TO POTENTIAL EQUILIBRIUM -- DATUM DATUM OWC OWC GOC -- DEPTH PRESS DEPTH PCOW DEPTH EQUIL 8400 4800 8500 0 8200 GOC RSVD RVVD PCOG TABLE TABLE SOLN METH 0 1 0 0 / -- VARIATION OF INITIAL RS WITH DEPTH -- DEPTH RS RSVD 8200 1.270 8500 1.270 / OUTPUT CONTROLS (SWITCH ON OUTPUT OF INITIAL GRID BLOCK PRESSURES) RPTSOL 1 11*0 / SUMMARY ------ THIS SECTION SPECIFIES DATA TO BE WRITTEN TO THE SUMMARY FILES ------ AND WHICH MAY LATER BE USED WITH THE ECLIPSE GRAPHICS PACKAGE EXCEL SEPARATE --REQUEST PRINTED OUTPUT OF SUMMARY FILE DATA RUNSUM --TOTAL OIL PRODUCTION - FIELD OIL PRODUCTION FOPR / -- WELL GAS-OIL RATIO FOR PRODUCER WGOR 'PRODUCER' / -- WELL BOTTOM-HOLE PRESSURE WBHP 'PRODUCER' -- GAS AND OIL SATURATIONS IN INJECTION AND PRODUCTION CELL

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-- WELL BOTTOM-HOLE PRESSURE WBHP 'PRODUCER' • GAS AND OIL SATURATIONS IN INJECTION AND PRODUCTION CELL -- GAS BGSAT 5 5 2 1 1 1 10 1 1 1 10 1 10 10 1 BOSAT 5 5 2 1 1 1 10 1 1 1 10 1 PRESSURE IN INJECTION AND PRODUCTION CELL -- PRE BPR 4 4 2 5 4 2 6 4 2 4 5 2 5 5 2 4 6 2 5 5 2 4 6 2 5 6 2 6 6 2 / SCHEDULE ______ THE SCHEDULE SECTION DEFINES THE OPERATIONS TO BE SIMULATED 0000 000 2 0 0 0000 000 000 1 --IMPES 1.0 1.0 10000.0 / -- SET 'NO RESOLUTION' OPTION -- DRSDT -- 0 / -- SET INITIAL TIME STEP TO 1 DAY AND MAXIMUM TO 6 MONTHS TUNING -__ GROUP LOCATION BHP PI NAME I J DEPTH DEFN WELL NAME -- NAME NOULER' G1' WELSPECS 'PRODUCER' G1' 'INJ1' G2' 'INJ2' G2' 'INJ3' G2' 'INJ4' G2' 5 5 1 1 10 1 1 10 10 10 8400 'OIL' 8335 'GAS' 8335 'GAS' 8335 'GAS' 8335 'GAS' / -- COMPLETION SPECIFICATION DATA -- WELL -- NAME COMPDAT -LOCATION- OPEN/ SAT CONN WELL I J K1 K2 SHUT TAB FACT DIAM 'PRODUCER' 5 5 3 3 'OPEN' 0 -1 0.5 / INJ1 INJ2 INJ3 INJ4 3 3 3 3 'OPEN' 1 'OPEN' 1 'OPEN' 1 'OPEN' 1 0.5 0.5 0.5 0.5 $\begin{array}{ccccccc} 1 & 1 & 3 \\ 10 & 1 & 3 \\ 1 & 10 & 3 \\ 10 & 10 & 3 \end{array}$ -1 -1 -1 -1 11 1 -- PRODUCTION WELL CONTROLS ___ ___ WELL NAME OPEN/ CNTL OIL SHUT MODE RATE WATER GAS LIQU RES RATE RATE RATE RATE BHP WCONPROD 4* PRODUCER' 'OPEN' 'BHP' 75000 1000 / 1 -- INJECTION WELL CONTROLS WELL NAME OPEN/ SHUT INJ TYPE CNTL MODE FLOW RATE WCONINJ INJ1 GAS INJ2 GAS INJ3 GAS INJ4 GAS OPEN OPEN OPEN OPEN 25000 25000 25000 25000 RATE / 'RATE 'RATE 'RATE 1 -- YEAR 1 TSTEP 1.0 14.0 13*25.0 TSTEP

-- YEAR 3 TSTEP 17*10.0 / TSTEP 12.5 -- 912.50 --> 1000.0 TSTEP 8.5 16*5.0 / TSTEP 5.0 / -- 1000.0 --> 1100.0 TSTEP 19*5.0 / TSTEP 5.0 -- 1100.0 --> 1200.0 TSTEP 19*5.0 / TSTEP 5.0 / IMPLICIT TUNING 10 / / TSTEP 10.0 /

END

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APPENDIX II

MATLAB

📝 Editor -	C:\Users\user\objective.m
File Edit	t Text Go Cell Tools Debug Desktop Window Help
: ") 🕝	📓 🕹 🍡 🛍 🤊 (* 🍓 🖅 - 🛤 🖛 🔶 ft, 💽 - 🗄 🏖 🖷 🐏 🗊 🕮 🍇 Stack:
**	- 1.0 + ÷ 1.1 × % ⁴ % ⁵ 0.
1 Ę	function z = objective (k)
2 -	<pre>qh = 7500-7000+7500+6700+4000-7900+9400+5400+4300-7600+4500+7800;</pre>
3 -	qs = 0.4359 * k(1) - 1.5920 * k(2) + 0.3575 * k(3) + 0.3797 * k(4) + 0.4359 * k(5) - 1.5920 * k(6)
4 -	+0.3575*k(7)+0.3797*k(8)+0.4359*k(9)-1.5920*k(10)+0.3575*k(11);
5 -	+0.3797*k(12);
6 -	$z = (qh - qs).^{2};$
7	
8	\$ 500;970;640;750;550;590;600;700;800;850;680;700
9	&UNTITLED Summary of this function goes here
10	S Detailed explanation goes here
11	<pre>% ,k2,k3,k4,k5,k6,k7,k8,k9,k10,k11,k12</pre>
12	<pre>% k1;k2;k3;k4;k5;k6;k7;k8;k9;k10;k11;k12</pre>
13	\$ [75000 75000 75000 67000 40000 79000 94000 54000 43000 76000 45000 78000]
14 -	end
15	
16	

File Help								
Problem Setup and Re	esults	Options						
Solver: ga - Genetic	Algorithm	Fitness limit:	🖲 Use default: -Inf					
Problem				C Specify:				
Fitness function:	@objective		Stall generations:	• Use default: 50				
Number of variables	: 12			C Specify:				
Constraints:			Stall time limit:	Use default: Inf				
Linear inequalities:	A:	b:		C Specify:				
Linear equalities:	Aeq:	beq:	Function tolerance:	• Use default: 1e-6				
Bounds:	Lower:	Upper:		C Specific				
Nonlinear constraint	t function:							
Run solver and view re	esults							
Use random state	s from previous run			C Specify:				
	T		Plot functions					
Start Paus	e Stop		Plot interval: 1					
Current iteration: 53		Clear Results	🔽 Best fitness 🛛 🗖	Best individual 🔽 Distance				
Optimization running.	÷	<u>^</u>	Expectation	Genealogy 🗖 Range				
Objective function value	e: 1.193131638234485E9			Searce Colortion				
Opumization terminated	average change in the intress value less than o	Suons, Toirun,	i Score diversity	Scores i Selection				
			Stopping	Max constraint				
		•	Custom function:					
Final point:			Output function	1				
1 - 2 3	4 5 6 7	8 9 10 11 12	Custom function:					
4.409 -12.539	6.574 7.378 5.496 -18.11 4.285	4.475 4.02 3.639 -5.334 -1.695	, custom function.					

APPENDIX III

Key Milestones



APPENDIX IV

Gantt Chart

NO	FYP1 activities/WEEK	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Selection of Project														
1	Торіс														
2	Preliminary Research														
	Work/ Literature														
	Review														
3	Methodology &														
	Planning														
	Extended Proposal														
4	Work														
	Submission Extended														
5	Proposal Defense														
6	Proposal Defence														
7	Developing														
	Conceptual Model														
8	Illustrating Forward														
	Model														
9	Results Analysis &														
	Report														
10	Submission of Interim														
	Report Draft														
11	Submission of Interim														
	Report														

NO	FYP2 activities/WEEK	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Developing synthetic model																	
2	Application of Evolutionary Algorithm																	
3	Set the threshold																	
4	Submission of Progress Report																	
5	Review and modification of result																	
6	Pre-SEDEX																	
7	Submission of Draft Final Report																	
8	Submission of Project Dissertation(SoftBound)																	
9	Submission of Technical Paper																	
10	Viva																	
11	Submission of Project Dissertation(Hard Bound)																	