ABDUL HADI BIN ABDUL RASHID

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Assisted History Matching by Using Genetic Algorithm and Discrete Cosine Transform

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UNIVERSITI TEKNOLOGI PETRONAS

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By

Abdul Hadi Bin Abdul Rashid

13960

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(Petroleum)

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Universiti Teknologi PETRONAS

Bandar Seri Iskandar

31750 Tronoh

Perak Darul Ridzuan

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CERTIFICATION OF APPROVAL

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A project dissertation submitted to the

Petroleum Engineering Programme

Universiti Teknologi PETRONAS

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BACHELOR OF ENGINEERING (Hons)

(PETROLEUM)

Approved by,

____

(Berihun Mamo Negash)

UNIVERSITI TEKNOLOGI PETRONAS

TRONOH, PERAK

May 2014

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.

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ABDUL HADI BIN ABDUL RASHID

ACKNOWLEDGEMENT

Praise be upon God Almighty, for with His will and permission, this Final Year Project entitled "Assisted History Matching by Using Genetic Algorithm and Discrete Cosine Transform has been completed successfully. This project is actually a part the requirements that the graduates of Geosciences & Petroleum Engineering Department have to fulfil in their final year. In my personal opinion, I feel that the programme is a great learning and hands-on experience for the future Petroleum Engineers that the university is aiming to produce.

I would like to express my deepest gratitude to my Mr. Berihun Mamo Negash, my project supervisor for his exemplary guidance and commitment in supervising me throughout the period. All his advices, remarks and assistance are highly appreciated. I am very grateful to have such an amazing mentor who is not just an expert on the matter, but is also dedicated.

Not to forget all the project coordinators for their effort and willingness in conducting the project throughout the two semesters period. Your assistance and guidance are truly helpful for us.

Last but not least, I would also like to thank all my friends who have given me motivations and assistance during completing this project.

Thank you.

ABSTRACT

Back in the days, before computers and IT were widely used, history matching was done manually by trial and error method, where personal judgment were very critical in undergoing such methodology. In other words, only highly-skilled and experienced engineers can perform history matching. Apart from that, the manual way consume too much time, especially when dealing with thousands of well parameters. Hence, this project, which propose the usage of assisted history matching technique with Genetic Algorithm (GA) as the optimization tool and Discrete Cosine Transform (DCT) as the parameter reduction method is carried out in order to achieve the objective of minimizing the time taken to do history matching.

To achieve the objective stated above, a conceptual reservoir model was built based on a set of average reservoir data. Next, fluid flow equations were derived to obtain the forward model and eventually, the objective function. Later, an algorithm combining both Genetic Algorithm and Discrete Cosine Transform was proposed, which shows the step-by-step sequence of both methods.

Overall, an algorithm showing the combination method of both GA and DCT was successfully developed. Then the proposed algorithm for DCT and GA can be applied to the history matching problem.

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CHAPTER 1
INTRODUCTION

1.1. Background

Reservoir simulation and modelling have been extensively used in the oil and gas industry with the means of determining the behavior of a reservoir and its production capability. They are some of the most efficient tool in the industry which combines mathematics, reservoir engineering, physics, and computer programming all into one[1]. The main goal of such technique is to predict the performance of a reservoir, which is very crucial in one company's income contribution. One of the methods that is widely used in reservoir management today is history matching (HM).

History matching can be defined as a process of adjusting and manipulating numerical reservoir parameters by utilizing reservoir simulation in order to match simulated model with the historical one. By doing so, one can forecast the behavior and performance of a reservoir. Among the first few studies of history matching was made by Kruger (1961), where he did a calculation on a reservoir's areal permeability distribution[2].

In general, history matching can be done either manually or automatically. Traditionally, it was carried out manually, where the engineers would adjust and calculate the parameters one by one before they can obtain the desired result. However, it was really time consuming since they had to deal with thousands of parameters for each reservoir[3]. The technique has been developed ever since. Now, history matching can be done automatically with computer platform and software. However, since it discards the human experience and knowledge factor, there's a high probability that the outcome could be in error.

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Apart from that, there is also assisted history matching, where engineers still have to calibrate the reservoir model but this time with the assistance of reliable optimization tool[3]. These optimization tools help to speed up the calculation process of a history matching problem. There are a number of optimization methods that can also be used to produce a simulated reservoir model. One of them is Genetic Algorithm (GA). These methods are to be repeated several times (if necessary) in order to minimize the difference between the simulated line and the historical line. Apart from that, several parameter reduction techniques such as Discrete Cosine Transform (DCT) and Principle Component Analysis (PCA) can be implemented to eliminate some of the unknown reservoir parameters which are less significant. By combining both the parameter reduction techniques and the optimization methods, history matching can be done accurately in a shorter period of time.

Many of the industries nowadays are trying to reproduce the actual physical system behavior by developing mathematical models. These models, which are based on certain parameterization and fundamental law of physics, are called forward model. Among the models and fundamental laws that are used in reservoir engineering are Darcy's law, Mass conservation law, Equation of state, Fourier Transform, etc. Although it is possible to solve certain engineering problems with forward model, there are still many cases, such as earth sciences, where it is not possible to do so as the system is not easy to be accessed[2].

Once we have the forward model, we can now proceed to the objective function developing process. Objective function is actually the difference between an observation data, or in this case, between the simulated lines and the historical lines. Among the popular formulas used in calculating objective function are Least-Square Formulation, Weighted Least-Square Formulation and Generalized Least-Square Formulation[2].

1.2. Problem Statement

Manual history matching involves a lot of manual try and error calculations. The approach is always time consuming since the engineers need to manually select and manipulate the

`

input data from thousands of reservoir parameter values for the simulation. Apart from that, often the outcome would result in uncertainties and hence, reliability is always questioned for the manual history matching process.

Assisted history matching has been developed since in order to improve the traditional history matching method. Now, we use computer software to vary the objective functions and at the same time, the engineers' knowledge and experience is also required to minimize the error of the simulation.

For this project of mine, Genetic Algorithm (GA) and Discrete Cosine Transform (DCT) methods in were displayed in history matching problem. Both of the methods mentioned have been used for quite some time in the oil and gas industry. For genetic algorithm, it is basically used to look into a "population" of possible solutions and choose the most optimum one. As for discrete cosine transform, it minimizes the number of the parameters that are used in the process. Both the genetic algorithm and the discrete cosine transform method are to be applied to give the simulation result as close as the real historical result.

1.3. Objective

The objective of this project is to apply Genetic Algorithm (GA) and Discrete Cosine Transform (DCT) method in history matching problem. In order to achieve that, first a simple set of reservoir production and pressure data were obtained after building a conceptual reservoir model of 10x10x3 grid blocks for simulation purpose. Apart from that, I also have to determine whether the combination of Genetic Algorithm and Discrete Cosine Transform is efficient in handling history matching problem. In the end, I expect to be able to match the simulated data with the synthetic production history data as close as possible.

1.4. Scope of Study

This project focusses more on the building of conceptual model and to illustrate the application of Genetic Algorithm and Discrete Cosine Transform onto the objective function. Then, the methods was also applied to the conceptual model built earlier. Lastly, the focus is also to develop an algorithm showing the flow of the combination of both GA and DCT.

1.5. Relevancy of the Project

This project is highly relevant to Petroleum Engineering because it is actually a huge part in reservoir simulation. Apart from that, this project is also relevant in terms of technology and application since a lot of operating companies have used history matching to predict the future production of their reservoir.

CHAPTER 2
BACKGROUND

2.1. History Matching

Few years back, the oil and gas industry approached a new reservoir simulation methodology, where the idea was to use history matching as an optimization tool in defining difference between the simulated data of a reservoir and its real one[3]. History matching is used to adjust a reservoir model until it closely matches a reservoir's simulated data with its past behavior[1, 2]. Apart from that, history matching can also be applied to accurately predict and evaluate the future oil production of a reservoir[4]. Traditionally, history matching problems were solved manually via trial and error approach, where they were usually time consuming. Due to lack of data and constraints, history matching problem is classified as an ill-posed inverse problem. Hence, making the engineers in charge of the calculations to face non-uniqueness issue while dealing with it[5]. That makes history matching process the most difficult and challenging phase in reservoir simulation[6].

In short, history matching is a very critical reservoir stimulation technique to build reservoir model and alter the parameter values with the aim of matching the stimulated data with the historical data.

2.2. Assisted History Matching

Assisted history matching were then introduced to produce a faster solution than the traditional history matching method, especially in dealing multiple history matched models[5]. Assisted history matching (or semi-automatic HM) is a fabrication process of an initial model with an early approximation of unknown reservoir parameters which later will go through a reduction process of an objective function that substitutes the mismatch

`

between calculated and observed response by adjusting the relevant parameter [2]. A few studies has shown that assisted history matching technique together with the optimization theory is able to cut down the cost and time consumed for a model calibration[6, 7].

Many papers have agreed that assisted history matching is a very convenient update to the old, manual history matching technique which is mainly used to predict the future production of a reservoir. Apart from that, it also cuts the total time taken to undergo the history matching process.

2.3. Optimization Tool: Genetic Algorithm

Among the optimization methods that are used in history matching today are Evolutionary Algorithm (EA), Genetic Algorithm (GA), Ensemble Kalman Filter (EnKF), Recursive Least Squares (RLS), and Bayesian method. The one that I was applying in my project is Genetic Algorithm. Early in the days, GA was developed and popularized by Goldberg from Darwin's "survival of the fittest" theory of evolution. The idea was then implemented to computational algorithm to solve problems related to objective function in natural fashion. It has been widely used as optimization method in other fields since then, including reservoir engineering[1, 8]. Almost similar to evolutionary algorithm, GA consists of its own step-by-step process namely selection, genetic operators (mutation and crossover) and termination.

Genetic Algorithm process can be broken into 4 steps:

1) Roulette Wheel Selection: The probability of picking a particular individual (parameter) in a maximization problem is stated as:

$$P_i = \frac{f_i}{\sum_{j=1}^{N} f_i}$$

2) Rank selection: The fittest/best parameter is more likely to be selected to proceed.
3) Blend Crossover: To generate offspring from 2 randomly picked individuals (parents).
4) Mutation & Elitism: The best parameters are compared and chosen. In the end, the number of best individuals kept is the parameter of the algorithm.

`

2.4. Parameter Reduction Method: Discrete Cosine Transform

A number of parameters reduction methods are also used together with the optimization tool mentioned above. They are Discrete Cosine Transform (DCT), Principle Component Analysis (PCA), and Zonation method. The one that I was applying is DCT. Basically, it is a Fourier-based transform and was first developed by Ahmed *et al.* (1997) in signal decorrelation[2]. Only later it was used in other fields such as image compression and history matching[2]. Apart from that, it was also said in [2] that DCT is applied (as parameter reduction) to remove high frequency data from the reservoir parameters which are insensitive to the production data.

According to [12], the DCT basis consists of real cosine function, so the complexity associated with the imaginary components of discrete Fourier Transform(DFT) is avoided. For a two dimensional gridblock (N_(x) and N_y) reservoir properties filed where each gridblock represents a single estimable parameter u(x,y), the to dimensional DCT v(r,s) has the following form [12]:

$$v(r,s) = \alpha(r)\alpha(s)\sum_{x=0}^{N_x=1}\sum_{y=0}^{N_y=1} u(x,y)\cos\left[\frac{(2x+1)r\pi}{2N_x}\right]\ cos\left[\frac{(2y+1)s\pi}{2N_y}\right]\quad where\ \alpha(r=0) = \sqrt{\frac{1}{N_x}}\, and\ \alpha(r\neq 0) = \sqrt{\frac{2}{N_x}}$$

2.5. Forward Model

Forward models are mathematical models which are based on certain parameterization and fundamental law of physics with the aim of reproducing the actual physical system behavior [2]. They are often used to calculate the required sensitivity of the observed quantities to the unknown parameters of an inverse problem [12]. Based on [2], two very important components which are required to estimate the unknown parameters are:

1) A reservoir simulator modelling the fluid flow through the porous media.
2) A rock physics model calculating the seismic respons

Forward model derivation.

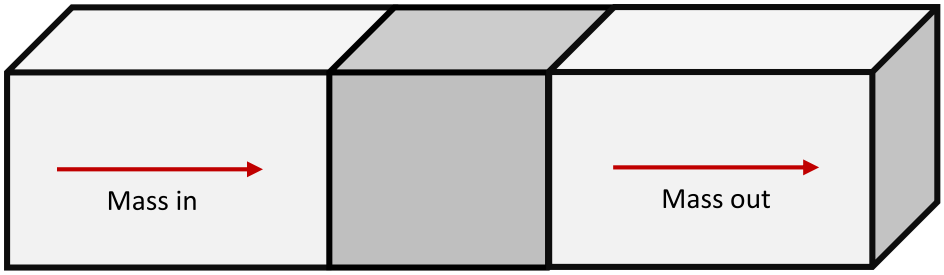

Figure 1: Simple reservoir blocks

Conservation of mass

$$\dot{m}\ in - \dot{m}\ out = rate\ of\ change\ of\ mass$$

$$-\frac{d}{dx}(\rho_l\, u_l) = \frac{d}{dt}(\Phi\rho_l S_l), \quad l = o, w$$

Darcy equation

$$u_l = -\frac{kk_{rl}}{\mu l}\frac{dP_l}{dx}\ , \quad l = o, w$$

Substitute darcy equation into mass balance equation

$$\frac{d}{dx}\left(\frac{kk_{ro}}{\mu_o B_o}\frac{dP_o}{dx}\right) - q_o = \frac{\acute{d}}{dt}\left(\frac{\Phi S_o}{B_o}\right)\ \ for\ oil$$

$$\frac{d}{dx}\left(\frac{kk_{rw}}{\mu_w B_w}\frac{dP_w}{dx}\right) - q_w = \frac{\acute{d}}{dt}\left(\frac{\Phi S_w}{B_w}\right)\ for\ water$$

P_{cow} = Po-Pw

So +Sw = 1

Left side flow term

$$\left(\frac{dPl}{dx}\right)_{i+1/2} = \frac{Pl_{i+1} - Pl_i}{\Delta x} - - - - - - -1\ \ \mathrm{l = o, w}$$

$$\left(\frac{dPl}{dx}\right)_{i-1/2} = \frac{Pl_i - Pl_{i-1}}{\Delta x} - - - - - - - - - - - - -2\ \ \mathrm{l = o, w}$$

Discretization of flow equation

`

Forward

$$\left[f(x)\frac{dP_l}{dx}\right]_{i+1/2} = \left[f(x)\frac{dP_l}{dx}\right]_i + \frac{\Delta x_{i/2}}{1!}\frac{d}{dx}\left[f(x)\frac{dP_l}{dx}\right]_i + \frac{\left(\Delta x_{\frac{i}{2}}\right)^2}{2!}\frac{d^2}{d^2x}\left[f(x)\frac{dP_l}{dx}\right]_i + \cdots \; \mathrm{l = o, w}$$

Backward

$$\left[f(x)\frac{dP_l}{dx}\right]_{i-1/2} = \left[f(x)\frac{dP_l}{dx}\right]_i + -\frac{\Delta x_{i/2}}{1!}\frac{d}{dx}\left[f(x)\frac{dP_l}{dx}\right]_i + \frac{\left(-\Delta x_{\frac{i}{2}}\right)^2}{2!}\frac{d^2}{d^2x}\left[f(x)\frac{dP_l}{dx}\right]_i + \cdots \mathrm{l = o, w}$$

Forward –backward and substitute equation 1 and 2

$$\frac{d}{dx}\left[f(x)\frac{dP_l}{dx}\right] = \frac{f(x)_{i+1/2}\frac{P_{i+1}-P_i}{\Delta x} - f(x)_{i-1/2}\frac{P_i - P_{i-1}}{\Delta x}}{\Delta x} \quad l = o, w$$

For oil

$$\frac{d}{dx}\left(\frac{kk_{ro}}{\mu_o B_o}\frac{dP_o}{dx}\right)_i \approx T_{xoi+\frac{1}{2}}(P_{oi+1} - P_{oi}) + T_{xoi-\frac{1}{2}}(P_{oi-1} - P_{oi})$$

For water

$$\frac{d}{dx}\left(\frac{kk_{rw}}{\mu_w B_w}\frac{dP_w}{dx}\right)_i \approx T_{xwi+\frac{1}{2}}(P_{wi+1} - P_{wi}) + T_{xwi-\frac{1}{2}}(P_{wi-1} - P_{wi})$$

$$T_{xoi+\frac{1}{2}} = \frac{2\lambda_{oi+1/2}}{\Delta x\left(\frac{\Delta x}{k_{i+1}} + \frac{\Delta x}{k_i}\right)} \qquad \lambda_o = \frac{k_{ro}}{\mu_{oB_o}}$$

Upstream Mobility

$\lambda_{oi+\frac{1}{2}} = \lambda_{oi+1}\ if\ P_{oi+1} \geq P_{oi}$ or $\lambda_{oi}\ if\ P_{oi+1} < P_{oi}$

$\lambda_{wi+\frac{1}{2}} = \lambda_{wi+1}\ if\ P_{wi+1} \geq P_{wi}$ or $\lambda_{wi}\ if\ P_{wi+1} < P_{wi}$

Right side term

For oil

$$\frac{d}{dt}\left(\frac{\Phi S_o}{B_o}\right) = \frac{\Phi}{B_o}\frac{dS_o}{dt} + S_o\frac{d}{dt}\left(\frac{\Phi}{B_o}\right)$$

$$\frac{d}{dt}\left(\frac{\Phi}{B_o}\right)_i \approx -\frac{\Phi_i}{\Delta t_{oi}}\left[\frac{c_r}{B_o} + \frac{d\left(\frac{1}{B_o}\right)}{dP_o}\right]_i (P_o^{t+\Delta t} - P_{oi}^t)$$

`

Standard backward approximation of time derivative

$$\left(\frac{\Phi}{B_o}\frac{dS_o}{dt}\right)_i \approx -\frac{\Phi_i}{B_{oi}\Delta t_i}(S_{wi}^{t+\Delta t} - S_{wi}^{t})$$

$$\frac{d}{dt}\left(\frac{\Phi S_o}{B_{oi}}\right)_i \approx\ C_{poq}\left(P_{oi}^{t+\Delta t} - P_{oi}^{t}\right) + C_{swoi}(S_{wi}^{t+\Delta t} - S_{wi}^{t})$$

$$C_{poq} = \frac{\Phi(1 - S_{wi})}{\Delta t}\left[\frac{c_r}{B_o} + \frac{d\left(\frac{1}{B_o}\right)}{dP_o}\right]_i$$

$$C_{swoi} = -\frac{\Phi_i}{B_{oi}\Delta t_i}$$

For water

$$\frac{d}{dt}\left(\frac{\Phi S_w}{B_w}\right) = \frac{\Phi}{B_w}\frac{dS_w}{dt} + S_w\frac{d}{dt}\left(\frac{\Phi}{B_w}\right)$$

$$\frac{d}{dt}\left(\frac{\Phi}{B_w}\right) = \frac{d}{dP_w}\left(\frac{\Phi}{B_w}\right)\frac{dP_w}{dt} = \frac{d}{dP_w}\left(\frac{\Phi}{B_w}\right)\left(\frac{dP_o}{dt} - \frac{dP_{cow}}{dt}\right)$$

$$\frac{d}{dt}\left(\frac{\Phi S_w}{B_w}\right)_i \approx C_{powi}\left(P_{oi}^{t+\Delta t} - P_{oi}^{t}\right) + C_{swwi}(S_{wi}^{t+\Delta t} - S_{wi}^{t})$$

$$C_{powi} = \frac{\Phi_i S_{wi}}{\Delta t}\left[\frac{c_r}{B_o} + \frac{d\left(\frac{1}{B_w}\right)}{dP_w}\right]_i$$

$$C_{swwi} = \frac{\Phi_i}{B_{wi}\Delta t_i} - \left(\frac{dP_{cow}}{dS_w}\right)_i C_{powi}$$

Discrete form of oil and water

For oil

$$T_{xoi+\frac{1}{2}}(P_{oi+1} - P_{oi}) + T_{xoi-\frac{1}{2}}(P_{oi-1} - P_{oi}) - \acute{q}_{oi} = C_{poq}\left(P_{oi}^{t+\Delta t} - P_{oi}^{t}\right) + C_{swoi}(S_{wi}^{t+\Delta t} - S_{wi}^{t})$$

For water

$$T_{xwi+\frac{1}{2}}[(P_{wi+1} - P_{wi}) - (P_{cowi+1} - P_{cowi})] + T_{xwi-\frac{1}{2}}[(P_{wi-1} - P_{wi}) - (P_{cowi-1} - P_{cowi})] - \acute{q}_{wi} = C_{powi}\left(P_{oi}^{t+\Delta t} - P_{oi}^{t}\right) + C_{swwi}(S_{wi}^{t+\Delta t} - S_{wi}^{t})$$

$$T_{xoi+\frac{1}{2}} = \frac{2\lambda_{oi+1/2}}{\Delta x\left(\frac{\Delta x}{k_{i+1}} + \frac{\Delta x}{k_i}\right)} \qquad T_{xoi-\frac{1}{2}} = \frac{2\lambda_{oi-1/2}}{\Delta x\left(\frac{\Delta x}{k_{i-1}} + \frac{\Delta x}{k_i}\right)}$$

$$T_{xwi+\frac{1}{2}} = \frac{2\lambda_{wi+1/2}}{\Delta x\left(\frac{\Delta x}{k_{i+1}}+\frac{\Delta x}{k_i}\right)} \qquad T_{xwi-\frac{1}{2}} = \frac{2\lambda_{wi-1/2}}{\Delta x\left(\frac{\Delta x}{k_{i+1}}+\frac{\Delta x}{k_i}\right)}$$

Combine the discrete form of oil and water by eliminating the saturation of water terms and arrange the equations

$$P_{oi-1}\left(T^t_{xoi-\frac{1}{2}} + \alpha_i T^t_{xoi-\frac{1}{2}}\right) + P_{oi}\left(-\left(T^t_{xoi+\frac{1}{2}} + T^t_{xoi-\frac{1}{2}} + C^t_{poq}\right) - \alpha_i\left(T^t_{xwi+\frac{1}{2}} + T^t_{xwi-\frac{1}{2}} + C^t_{powi}\right)\right) + P_{oi+1}\left(T^t_{xoi+\frac{1}{2}} + \alpha_i T^t_{xwi+\frac{1}{2}}\right) = -\left(C^t_{pooi} + \alpha_i C^t_{powi}\right)P^t_{oi} + \acute{q}_{oi} + \alpha_i \acute{q}_{wi} + \alpha_i T^t_{xwi+\frac{1}{2}}(P_{cowi+1} - P_{cowi})^t + \alpha_i T^t_{xwi-\frac{1}{2}}(P_{cowi-1} - P_{cowi})^t$$

$$a_i P_{oi-1} + b_i P_{oi} + c_i P_{oi-1} = d_i$$

$$a_i = T^t_{xoi-\frac{1}{2}} + \alpha_i T^t_{xoi-\frac{1}{2}}$$

$$b_i = -\left(T^t_{xoi+\frac{1}{2}} + T^t_{xoi-\frac{1}{2}} + C^t_{poq}\right) - \alpha_i\left(T^t_{xwi+\frac{1}{2}} + T^t_{xwi-\frac{1}{2}} + C^t_{powi}\right)$$

$$c_i = T^t_{xoi+\frac{1}{2}} + \alpha_i T^t_{xwi+\frac{1}{2}}$$

$$d_i = -\left(C^t_{pooi} + \alpha_i C^t_{powi}\right)P^t_{oi} + \acute{q}_{oi} + \alpha_i \acute{q}_{wi} + \alpha_i T^t_{xwi+\frac{1}{2}}(P_{cowi+1} - P_{cowi})^t + \alpha_i T^t_{xwi-\frac{1}{2}}(P_{cowi-1} - P_{cowi})^t$$

$$\alpha = -\frac{C^t_{swwi}}{C^t_{swoi}}$$

Boundary condition for production at bottom hole pressure specified well condition

$$q_{o\iota} = \frac{WC_\iota}{A\Delta x}\acute{\lambda}_{o\iota}(P_{o\iota} - P_{bh\iota})$$

$$q_{w\iota} = \frac{WC_\iota}{A\Delta x}\acute{\lambda}_{w\iota}(P_{w\iota} - P_{bh\iota})$$

Substitute boundary condition to the equation

$$P_{oi-1}\left(T^t_{xoi-\frac{1}{2}} + \alpha_i T^t_{xoi-\frac{1}{2}}\right) + P_{oi}\left(-\left(T^t_{xoi+\frac{1}{2}} + T^t_{xoi-\frac{1}{2}} + C^t_{poq} + \frac{WC_i}{A\Delta x}\lambda_{oi}\right) - \alpha_i\left(T^t_{xwi+\frac{1}{2}} + T^t_{xwi-\frac{1}{2}} + C^t_{powi} + \frac{WC_i}{A\Delta x}\lambda_{wi}\right)\right) + P_{oi+1}\left(T^t_{xoi+\frac{1}{2}} + \alpha_i T^t_{x\ \ldots 1}\right) = -\left(C^t_{pooi} + \alpha_i C^t_{powi}\right)P^t_{oi} - \frac{WC_i}{A\Delta x}\lambda_{oi}P_{bhi} - \alpha_i \frac{WC_i}{A\Delta x}\lambda_{wi}P_{bhi} + \alpha_i T^t_{xwi+\frac{1}{2}}(P_{cowi+1} - P_{cow} \quad {}_i T^t_{xwi-\frac{1}{2}}(P_{cowi-1} - P_{cowi})^t$$

`

$$a_i = T^t_{xoi-\frac{1}{2}} + \alpha_i T^t_{xoi-\frac{1}{2}}$$

$$b_i = -\left(T^t_{xoi+\frac{1}{2}} + T^t_{xoi-\frac{1}{2}} + C^t_{poq} + \frac{WC_i}{A\Delta x}\lambda_{oi}\right) - \alpha_i\left(T^t_{xwi+\frac{1}{2}} + T^t_{xwi-\frac{1}{2}} + C^t_{powi} + \frac{WC_i}{A\Delta x}\lambda_{wi}\right)$$

$$c_i = T^t_{xoi+\frac{1}{2}} + \alpha_i T^t_{xwi+\frac{1}{2}}$$

$$d_i = -\left(C^t_{pooi} + \alpha_i C^t_{powi}\right)P^t_{oi} - \frac{WC_i}{A\Delta x}\lambda_{oi}P_{bhi} - \alpha_i \frac{WC_i}{A\Delta x}\lambda_{wi}P_{bhi} + \alpha_i T^t_{xwi+\frac{1}{2}}(P_{cowi+1} - P_{cowi})^t + \alpha_i T^t_{xwi-\frac{1}{2}}(P_{cowi-1} - P_{cowi})^t$$

2.6. Objective Function

According to [2], objective function can be defined as the amount of discrepancy (difference) between simulated and measured data for a given set of data. There are three formulas which are generally used to calculate objective function:

1) Least square formulation

$$F = (d^{obs} - d^{cal})^T (d^{obs} - d^{cal})$$

2) Weighted least square formulation

$$F = (d^{obs} - d^{cal})^T w (d^{obs} - d^{cal})$$

3) Generalized least square formulation

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

Based on [9], α is assumed to be constant and it is a function of location x and time t and is parameterized by permeability k.

$$P_j^{n+1} = P_j^n + \alpha \frac{\Delta t}{\Delta x^2}\left\{P_{j+1}^n - 2P_j^n + P_{j-1}^n\right\}$$

For a uniform time and space grid, the objective function used is the least square type and it is as below:

$$Q = \sum_{n=1}^{t}\left\{P_j^{obs,n} - P_j^{calc,n}\right\}^2$$

According to [9], after derivation of diffusivity equation, the objective function is as follow:

$$R(t) = \alpha(t)F(t)$$

`

CHAPTER 3
LITERATURE REVIEW

3.1. Introduction

History matching contains non-uniqueness issue as it is an ill-posed inverse problem as it is insufficient in data and constraints [5]. In fact, based on [6], it is said that history matching is, without doubt, the hardest part of reservoir simulation. Hence, it is very critical for reservoir engineers to apply parameter reduction and optimization methods in solving a history matching problem [12].

3.2. Application in Reservoir Simulation and other industries

3.2.1. Genetic Algorithm

According to[1], GA was first introduced by John Henry Holland for experimenting adaptive behaviors which later was known as Holland’s Schema Theorem. It was later developed and popularized by Goldberg from Darwin’s “survival of the fittest” theory of evolution[8]. It has then been commonly used in history matching as one of the optimization methods since then.

Based on [2], optimization methods can be sub-divided into 3, namely gradient based method, non-gradient based method, and global minima. GA falls under the third category.

However, based on [*Oliver et al*., 2008], it was stated that applying genetic algorithm onto history matching problems can be computationally expensive. Apart from that, they also mentioned that the algorithm could require a lot of iterations before getting the desired matching reservoir production data. Despite all that, study in [1] showed that success in applying GA to match the simulated data with the historical data could be achieved, with

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the right combination of mutation rate, crossover rate and generation number. In my opinion, GA could be an alternative for history matching's optimization tools for today's application.

3.2.2. Discrete Cosine Transform

[12] stated that before optimizing the thousands of grid blocks of a real reservoir, it is very much necessary to minimize unnecessary parameters using parameter reduction methods. There are a few numbers of parameter reduction methods that can be used such as Zonation, Principle Component Analysis and Discrete Cosine Transform (DCT). I am using DCT for this project.

DCT is actually a Fourier based transform and its first application was first introduced for signal decorrelation, and later for image compression [2]. It is also stated in there that it is commonly used to minimize the amount of data where it uses the principle of orthonormal cosine transform [11]. In my opinion, this method is a very good alternative for reducing parameters since it would need fewer assumptions [12], hence fewer time to complete this phase.

In image compression, DCT is commonly used to store large amount of data by separating images into different parts with different frequencies. Only in the quantization step that less significant frequencies is discarded, leaving fewer number of parameters to be computed in the next step. This idea would definitely fit into history matching, especially when dealing with thousands of reservoir parameters, from thousands of reservoir grid blocks.

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3.3. Demonstration and example

3.3.1. Demonstration of Genetic Algorithm method on Mathematical Equality Problem

For this example, we will use the equality:

$$a + 2b + 3c + 4d = 30$$

The equation is used to determine the value of a, b, c and d using genetic algorithm method. The first step is to formulate the above equation into an objective function where:

$$F(x) = [(a + 2b + 3c + 4d) - 30]$$

In this example, the four variables are composed as parameter namely a, b, c and d. Apart from that, we will restrict the value of the four variables a, b, c, and d as integers between 0 and 30.

Step 1: Initialization

For this example, we set the number of parameters as 6, and we generate random numbers of all the genes for the 6 parameters.

Parameter 1 = [a;b;c;d] = [12;05;23;08]

Parameter 2 = [a;b;c;d] = [02;21;18;03]

Parameter 3 = [a;b;c;d] = [10;04;13;14]

Parameter 4 = [a;b;c;d] = [20;01;10;06]

Parameter 5 = [a;b;c;d] = [01;04;13;19]

Parameter 6 = [a;b;c;d] = [20;05;17;01]

Step 2: Evaluation

Next, we compute the objective function for all the parameters from above:

Objective Function 1 = Abs[(12 + 2(05) + 3(23) + 4(08)) – 30] = **93**

`

Objective Function 2 = Abs[(02 + 2(21) + 3(18) + 4(03)) – 30] = **80**

Objective Function 3 = Abs[(10 + 2(04) + 3(13) + 4(14)) – 30] = **83**

Objective Function 4 = Abs[(20 + 2(01) + 3(10) + 4(06)) – 30] = **46**

Objective Function 5 = Abs[(01 + 2(04) + 3(13) + 4(19)) – 30] = **94**

Objective Function 6 = Abs[(20 + 2(05) + 3(17) + 4(01)) – 30] = **55**

Step 3: Selection

In genetic algorithm, the fittest parameter will have higher chances to be selected to undergo the next process. Therefore, we must calculate the fitness of each parameter. (To avoid zero problem, the value for each objective function is added by 1)

Fitness 1 = $\left(\frac{1}{1+Objective\ Function\ 1}\right) = \left(\frac{1}{1+93}\right)$ = **0.0106**

Fitness 2 = $\left(\frac{1}{1+Objective\ Function\ 2}\right) = \left(\frac{1}{1+80}\right)$ = **0.0123**

Fitness 3 = $\left(\frac{1}{1+Objective\ Function\ 3}\right) = \left(\frac{1}{1+83}\right)$ = **0.0119**

Fitness 4 = $\left(\frac{1}{1+Objective\ Function\ 4}\right) = \left(\frac{1}{1+46}\right)$ = **0.0213**

Fitness 5 = $\left(\frac{1}{1+Objective\ Function\ 5}\right) = \left(\frac{1}{1+94}\right)$ = **0.0105**

Fitness 6 = $\left(\frac{1}{1+Objective\ Function\ 6}\right) = \left(\frac{1}{1+55}\right)$ = **0.0179**

Total = 0.0106 + 0.0123 + 0.0119 + 0.0213 + 0.0105 + 0.0179 = **0.0845**

Hence, the probability for every parameter is:

Probability 1 = $\left(\frac{0.0106}{0.0845}\right)$ = **0.1254**

Probability 2 = $\left(\frac{0.0123}{0.0845}\right)$ = **0.1456**

Probability 3 = $\left(\frac{0.0119}{0.0845}\right)$ = **0.1408**

Probability 4 = $\left(\frac{0.0213}{0.0845}\right)$ = **0.2521**

Probability 5 = $\left(\frac{0.0105}{0.0845}\right)$ = **0.1243**

`

Probability 6 = $\left(\frac{0.0179}{0.0845}\right)$ = **0.2118**

From the above values, we can tell that parameter 4 has the highest fitness, hence the highest probability to get selected for the next generation parameters.

Step 4: Selection

For this step, we use roulette wheel approach, where we first have to calculate the cumulative probability values:

Cumulative 1 = 0.1254

Cumulative 2 = 0.1254 + 0.1456 = 0.2710

Cumulative 3 = 0.1254 + 0.1456 + 0.1408 = 0.4118

Cumulative 4 = 0.1254 + 0.1456 + 0.1408 + 0.2521 = 0.6639

Cumulative 5 = 0.1254 + 0.1456 + 0.1408 + 0.2521 + 0.1243 = 0.7882

Cumulative 6 = 0.1254 + 0.1456 + 0.1408 + 0.2521 + 0.1243 + 0.2118 = 1.0

The next step is to generate random number integer between 0-1. They are:

Random 1 = 0.201

Random 2 = 0.284

Random 3 = 0.099

Random 4 = 0.822

Random 5 = 0.398

Random 6 = 0.501

If random number 1 is greater than Probability 1 and smaller than Probability 2, then select Parameter 2 as the parameter in the new population for the next generation:

New Parameter 1 = Parameter 2

New Parameter 2 = Parameter 3

New Parameter 3 = Parameter 1

New Parameter 4 = Parameter 6

New Parameter 5 = Parameter 3

`

New Parameter 6 = Parameter 4

Parameter in the population thus became:

Parameter 1 = [02;21;18;03]

Parameter 2 = [10;04;13;14]

Parameter 3 = [12;05;23;08]

Parameter 4 = [20;05;17;01]

Parameter 5 = [10;04;13;14]

Parameter 6 = [20;01;10;06]

Step 5: Crossover

For the next step, we use one-cut point, where we randomly select a position in the parent parameter then exchanging the values of the sub-parameters. Parent parameters which will mate are randomly selected and the number of mate Parameters is controlled using crossover rate parameters. For this example, we set the crossover rate at 25% or 0.25. Then, we again generate random numbers between 0 and 1. Whichever is/are below the crossover rate are to be selected to undergo the crossover process:

Random 1 = 0.191

Random 2 = 0.259

Random 3 = 0.760

Random 4 = 0.006

Random 5 = 0.159

Random 6 = 0.340

Among the random numbers above, Parameter [1], Parameter [4] and Parameter [5] are selected for crossover. Hence, the crossover are between:

Parameter 1 X Parameter 4

Parameter 4 X Parameter 5

Parameter 5 X Parameter 1

`

The next process is to determine the position of the crossover point. First, we will have to generate random numbers between 1 to (length of Parameter – 1). In this example, the generated random numbers should be in the range of 1 and 3. After we get the crossover point, parent parameters are cut at crossover point and its genes are interchanged. The three random numbers are:

Random 1 = 1

Random 2 = 1

Random 3 = 2

From the above generated random numbers, parent's genes are cut at gene number 1 (for both parameter 1 and parameter 4) and gene number 3 (for parameter 5) respectively, e.g.

Parameter 1 = Parameter 1 X Parameter 4

= [02;21;18;03] X [20;05;17;01]

= [02;05;17;01]

Parameter 4 = Parameter 4 X Parameter 5

= [20;05;17;01] X [10;04;13;14]

= [20;04;13;14]

Parameter 5 = Parameter 5 X Parameter 1

= [10;04;13;14] X [02;21;18;03]

= [10;04;18;03]

Hence, The new parameter population after undergoing the crossover process are:

Parameter 1 = [02;05;17;01]

Parameter 2 = [10;04;13;14]

Parameter 3 = [12;05;23;08]

Parameter 4 = [20;04;13;14]

Parameter 5 = [10;04;18;03]

Parameter 6 = [20;01;10;06]

`

Step 6: Mutation

In this step, gene at random position are replaced with a new value. First we must calculate the total length of gen in the population. In this case the total length of gen is total gene = number of genes in Parameter * number of population

= 4 * 6

= 24

Next, generate a random number between 1 and total genes (1 to 24). If generated random number is smaller than mutation rate variable, then marked the position of gen in parameters. Suppose we define the mutation rate at 10% or 0.10, it is expected that 10% (0.1) of total genes in the population that are mutated: number of mutations = 0.1 * 24

= 2.4

≈ 2

Again, random number have to be generated to determine the position of the switch to happen. Let's say the random numbers (which should be between 1 and 24) are 12 and 18. Meaning, the random mutation number are switched at Parameter number 3 gen number 4 and Parameter 5 gen number 2. The value of the mutated genes are also randomly generated. Hence, the parameters are now:

Parameter 1 = [02;05;17;01]

Parameter 2 = [10;04;13;14]

Parameter 3 = [12;05;23;02]

Parameter 4 = [20;04;13;14]

Parameter 5 = [10;05;18;03]

Parameter 6 = [20;01;10;06]

Step 7: Iteration

As a result, now we have one iteration of the genetic algorithm method. Hence, we evaluate the objective function:

New Objective Function 1 = Abs[(a + 2b + 3c + 4d) – 30] = 37

New Objective Function 2 = 77

`

New Objective Function 3 = 47

New Objective Function 4 = 93

New Objective Function 5 = 56

New Objective Function 2 = 46

The objective functions are decreasing, which means we have better parameter compared with previous parameter generation. The new parameters will undergo all the same process where it will produce again new generation of parameter for the next iteration. It will continue until a predetermined number of generations is set. For this example, after 50 iterations, we obtained:

Parameter = [07;05;03;01]

Where;

A + 2b + 3c + 4d

= 07 + 2(05) + 3(03) + 4(01)

= **30**

The value obtained from the last iteration satisfy the equality.

3.3.2. Demonstration of DCT in Image Compression

The following are the steps that have to be carried out for the application of Discrete Cosine Transform. Firstly, the image needs to be broken down into 8x8 blocks of pixels. Then, we need to work from left to right and top to bottom in order to apply DCT onto each block. Quantization are used afterwards to compress the image on each blocks. The array of compressed blocks that constitute the image is stored in a drastically reduced amount of space

According to [13], for a common 8x8 block:

$$D\ (i,j) = \frac{1}{\sqrt{2N}} C(i)C(j) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} p(x,y) \cos\left[\frac{(2x+1)i\pi}{16}\right] \cos\left[\frac{(2y+1)j\pi}{16}\right]$$

`

$$C(u) = \begin{Bmatrix} \frac{1}{\sqrt{2}}\ if\ u = 0 \\ 1\ if\ u > 0 \end{Bmatrix}$$

Where the following equation was used to obtain the matrix form, namely T matrix:

$$T_{i,j} = \begin{Bmatrix} \frac{1}{\sqrt{N}} & if\ i = 0 \\ \sqrt{\frac{2}{N}} cos\left[\frac{(2j+1)i\pi}{2N}\right] & if\ i > 0 \end{Bmatrix}$$

Next, M matrix, or the optimum DCT value need to be obtained. This value was used to level off the original value of each parameter by subtracting them off. Once we have both T and M matrix, DCT can be carried our using the following equation.

D = T*M*T'

The quantization phase will take place next, where it will basically determine the significant value/data that will survive. The last step is the data reconstruction phase. This is done by multiplying the compressed matrix with the quantization matrix. The result of the multiplication will then be added with the optimum DCT value, which was used earlier to level off the original value of each parameter.

Reconstructed Data, R = [Compressed Matrix (C) * Quantizer (Q)] + DCT value

3.4. Previous Study

Assisted history matching has been extensively developed and practiced all over the world. In [10], a combination of Bayesian, Markov Chain Monte Carlo (McMc) and DCT methods were applied on Mauddud Reservoir of Sabriyah Oil Field in Kuwait. The paper highlighted the application of assisted history matching in a structurally complex carbonate reservoir with the goal of predicting 8 years of oil production into the future.

`

Study [1] was made on the application of GA in history matching problem. The 2D reservoir model used, which contains 4 injector wells and 1 producer well, is made of 9 x 9 grid blocks, with the sizing of 200m (in area) and 20m in depth. Later, 3 synthetic history data were generated, with different permeability values. Later, GA was applied onto the three models, where different generation numbers, popularity sizes, mutation rates and crossover rates were used, totaling up to 10 different scenarios. In the end, the result showed that the combination of 5% mutation rate, 40% crossover rate (for roulette wheel selection phase) and 80% crossover rate (for rank selection phase) produced the best results.

As for DCT, [12] showed that DCT is quite effective when it was used as a parameterization method. The study aims to determine the best method to go with when it comes to parameter reduction. The reservoir was broken down into 64x64 grid blocks first before DCT and another Fourier-based transform, Karhunen-Loeve Transform were applied. In the end, the study found that DCT is more effective in terms of history matching parameterization option, especially when applied to vertical permeability.

`

CHAPTER 4
METHODOLOGY

Firstly, a simple set of reservoir data need to be obtained before producing a conceptual reservoir model using a reservoir simulator software. The model, which consists of 100 grid blocks, has as many unknown reservoir parameters as the number of blocks and the number of heterogeneous properties. In this model, each layer was divided into four zones where each zone is consisted of 10x10x3 grid blocks. This model consists of one production well and four injection wells.

DCT was first be applied in order to cut down the number of the parameters, hence minimizing the time consumption for the history matching problem. Later, GA method was implemented to solve the inverse history matching problem of the project. A computer programming language are used to code the calculation programmes. A graph was also generated consisting both the simulated and the observed data, where the difference between both curves was calculated and compared. If the difference is more than the setting threshold, the steps are repeated from using DCT to threshold calculation.

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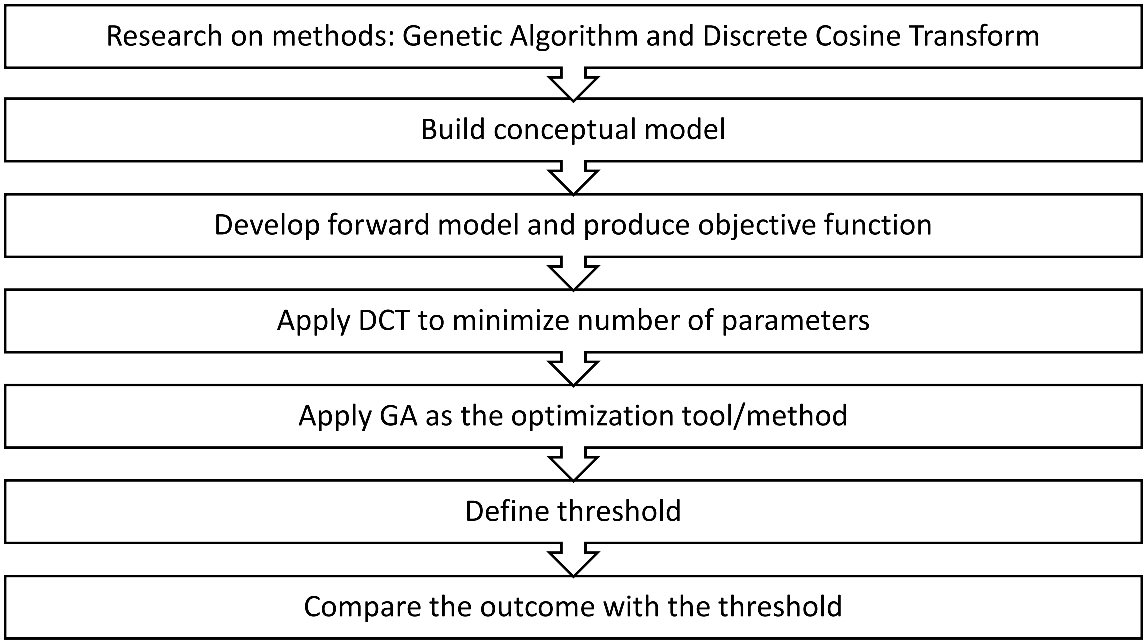

Figure 2: Brief outline of the methodology

1) Building a Conceptual model
   - Collect all the required data from a local reservoir (real reservoir data) and use them to build the conceptual model.
   - Conceptual model is built using ECLIPSE software by modifying existed reservoir.
   - The model coding can be found in “appendix” section.

2) Develop a forward model
   - Two-phase forward model is obtained from the derivation of mass balance, fluid flow and Darcy’s equation.
   - The derived equation can be found in “summary of project progress” section.

3) Create objective function from the forward model
   - Objective function is created based on the derived forward model.
   - The objective function is done based on least square formulation.

4) Apply Discrete Cosine Transform
   - DCT is used to minimize the number of parameters based on their significance.

5) Apply Genetic Algorithm

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- A graph was drawn (stimulated data vs historical data) by using the reduced number of parameters.
- GA is applied to optimize the parameters.

6) Calculate the threshold
   - Set the threshold value
   - The model parameters such as flow rate was compared with the historical data
   - If the threshold value is bigger than the set threshold, the steps of history matching is to be repeated again from steps 4 to 6

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CHAPTER 5

RESULTS & DISCUSSION

5.1. Synthetic Model

Some minor modification was made to one ODEH data in order to produce a model of a reservoir field. Compared to the original ODEH data, which had one producer well and one injector well, the new modified field has 5 wells instead. The configuration of the modified ODEH model is as follow:

Table 3: Well Coordinates

Well	**Coordinate (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

(Dimension: 10 x 10 x 3 grid blocks)

Size:

DX = 300 x 1000;

DY = 300 x 1000 ;

DZ = 100 x 20 (first layer); 100 x 20 (second layer); 100 x 80 (third layer)

Phase present in reservoir: 4 (Oil, water, gas and dissolve gas)

Porosity, Φ = 0.3

`

The permeability varies for each layer. In this model, each layer was divided into four zones where each zone is consisted of 25 grid blocks. Each zone was set its own permeability value. After the model is build, sensitivity analysis is carried out in order to test the capabilities of the model to detect any changes happen to any of the reservoir parameters.

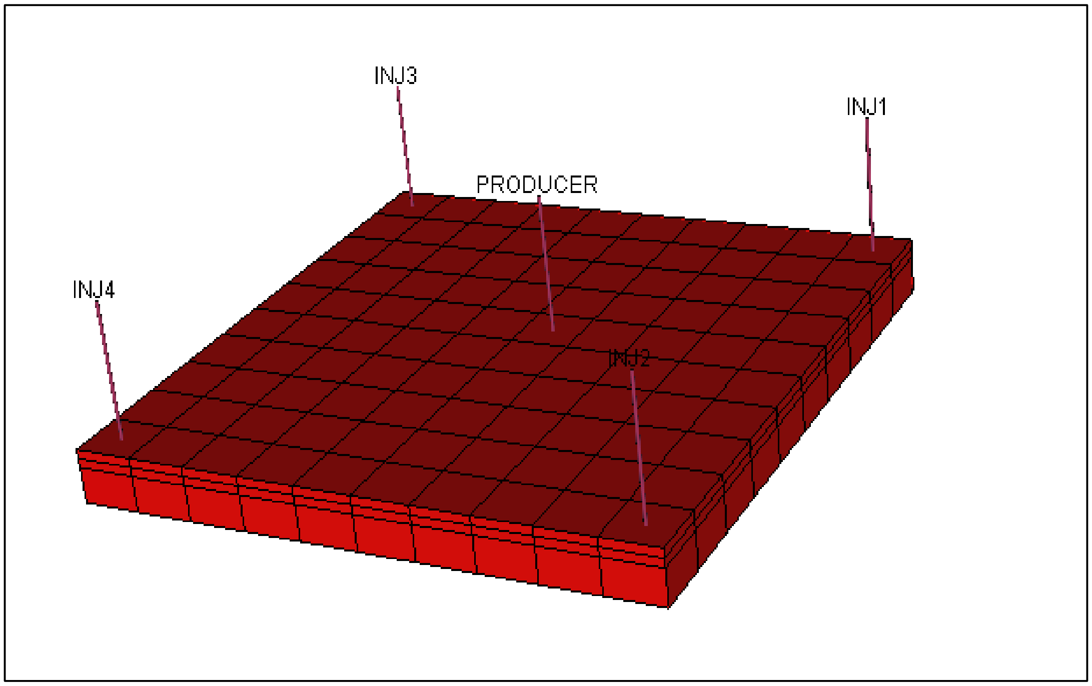

Figure 3: Model Configuration

In order to determine whether the changes made onto the reservoir parameters will affect the result from the model or not, sensitivity analysis was done. To do so, permeability values of each zone were changed and it's the eventual effect to the reservoir total oil production was recorded. If there are changes seen on the reservoir model, it shows that the model can be used for this project as it actively detect the changes made.

Methodology

The first change that was made onto the reservoir was the permeability value in the Dx direction. This is applied to every zone in every layer. The process was repeated 5 times, which the permeability ranges from: 100 – 400 mD, 500 – 800 mD, 900 – 1200 mD, 1300 – 1600 mD, and 1700- 2000 mD. Then, the flow rate (production data) from the simulation

`

was recorded before constructing a graph of total oil production data for every range of permeability. From the graph, we can conclude that the model is an active model as the difference between each curve in the graph is clear.

Flow Test

It is crucial for this simulation that the reservoir model is able to produce oil. Hence, flow test was conducted onto the model.

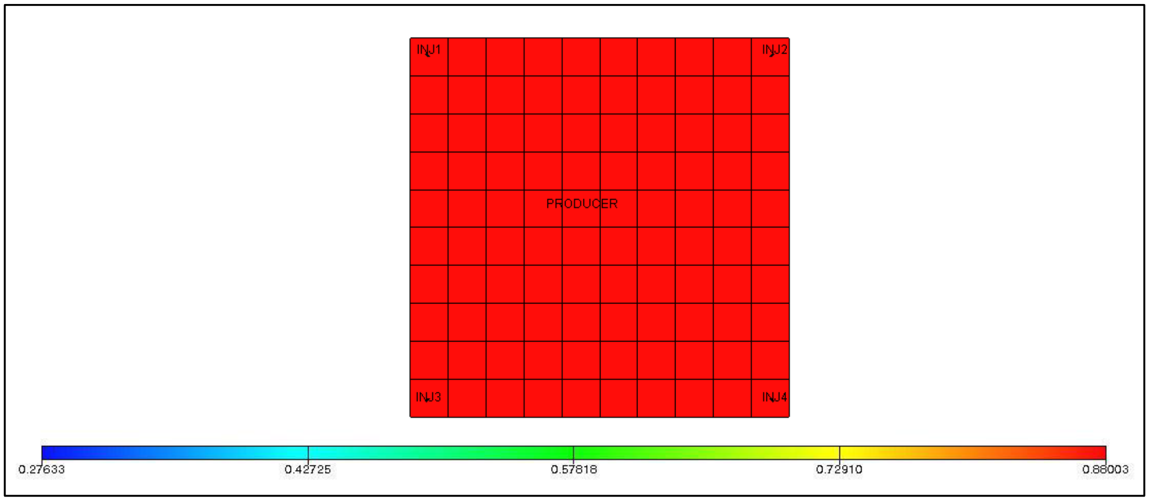

Figure 4: Before flow test

Before the test was conducted, we can see that the reservoir is 100% saturated with oil. Then, as we start with the flow test, we can see that:

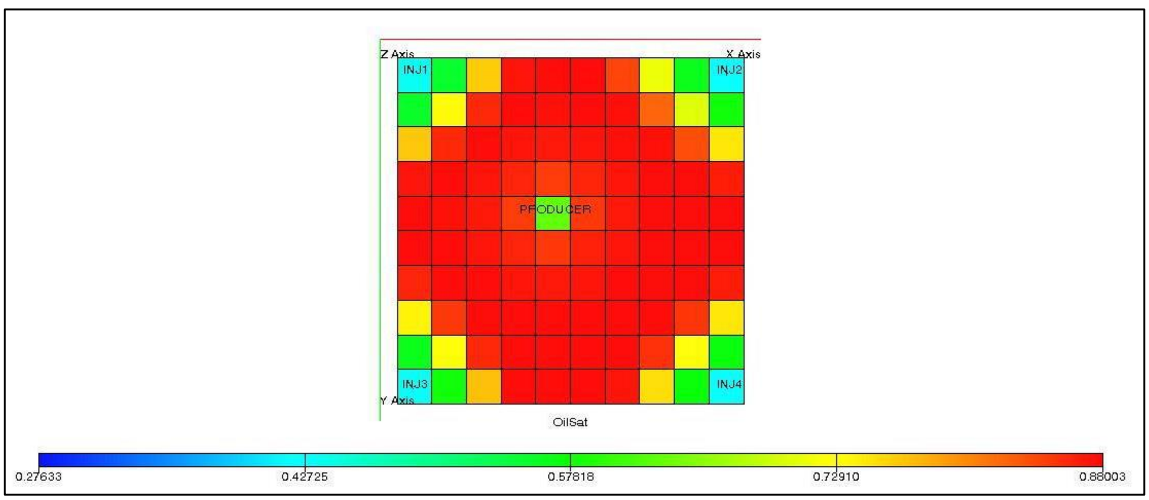

Figure 5: During flow test

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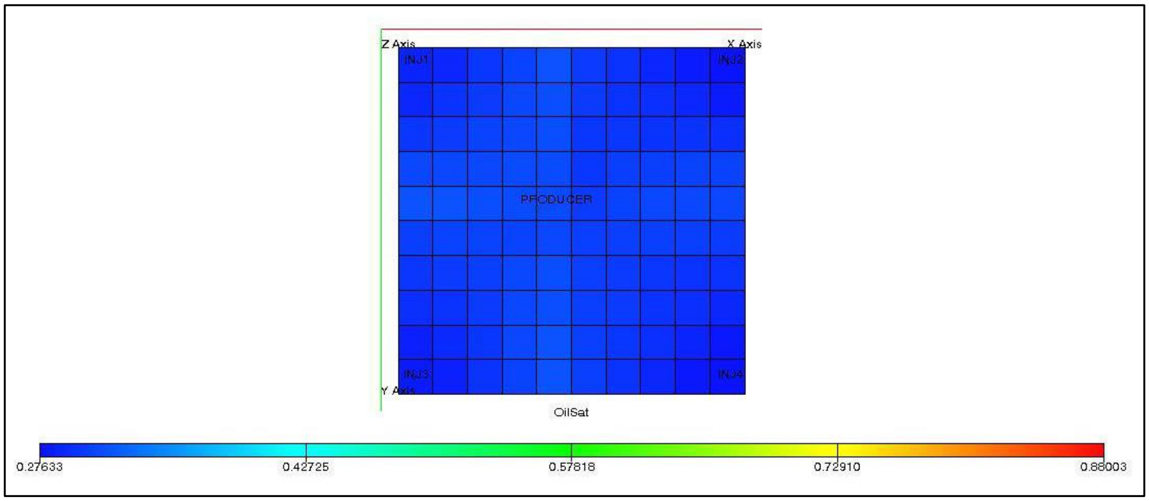

Figure 6: End of flow test

From the above pictures, we can see that water was filling the first two top layers of the model, starting from the injector areas. Apart from that, we can also see that oil saturation decreased in each layer, especially at the injector and producer areas.

History Data vs. Simulated Data

In order to obtain a set of history data, some minor modifications were made onto the ODEH data. Afterwards, we change the permeability value at every zone to represent the simulated data. The field total oil production rate and production rate graphs were plotted using Office software in Eclipse.

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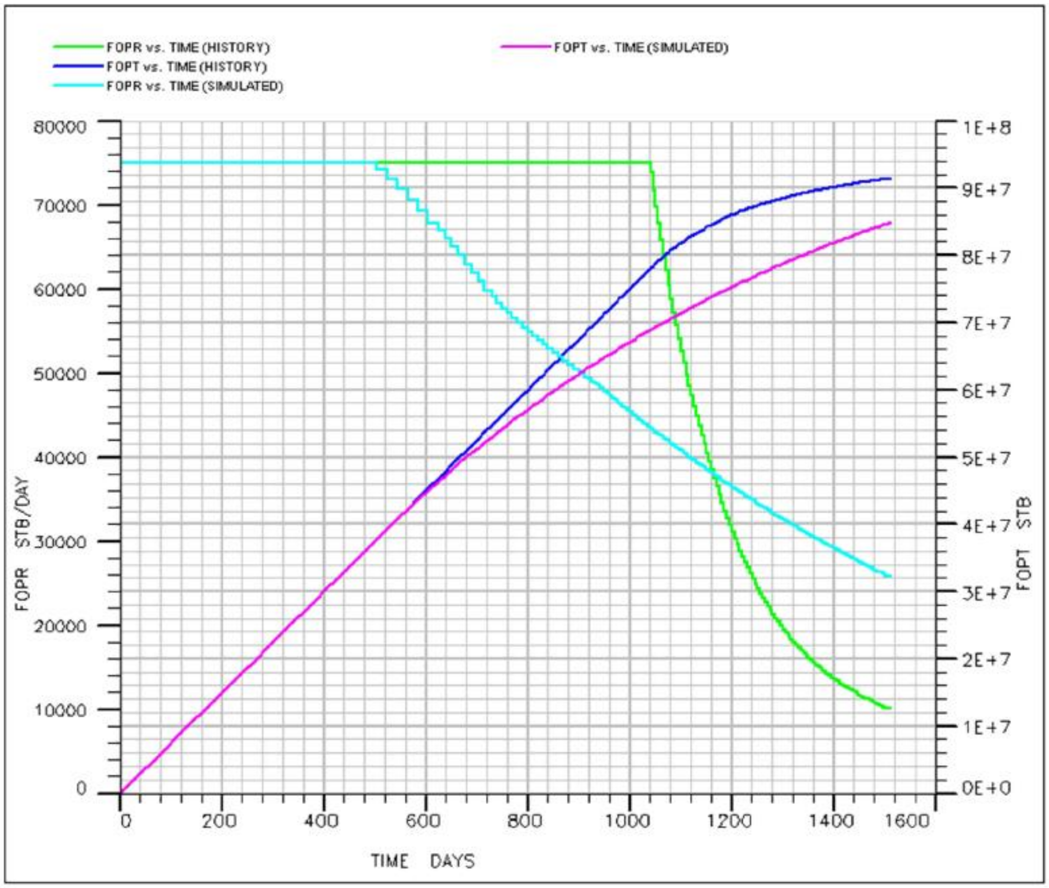

Figure 7: Total Oil Production Rate & Oil Production Rate vs. Time

We can see from the graph that there is a clear difference between the total oil produced curve for history and simulated data. From this data, the objective next is to match the simulated data line with the history data line. For my project, I use Genetic Algorithm and Discrete Cosine Transform methods to achieve that, with the aid of Matlab software for programme coding purposes.

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5.2. Proposed Algorithm

The diagram below (figure 6) discusses the flow process of the project in general.

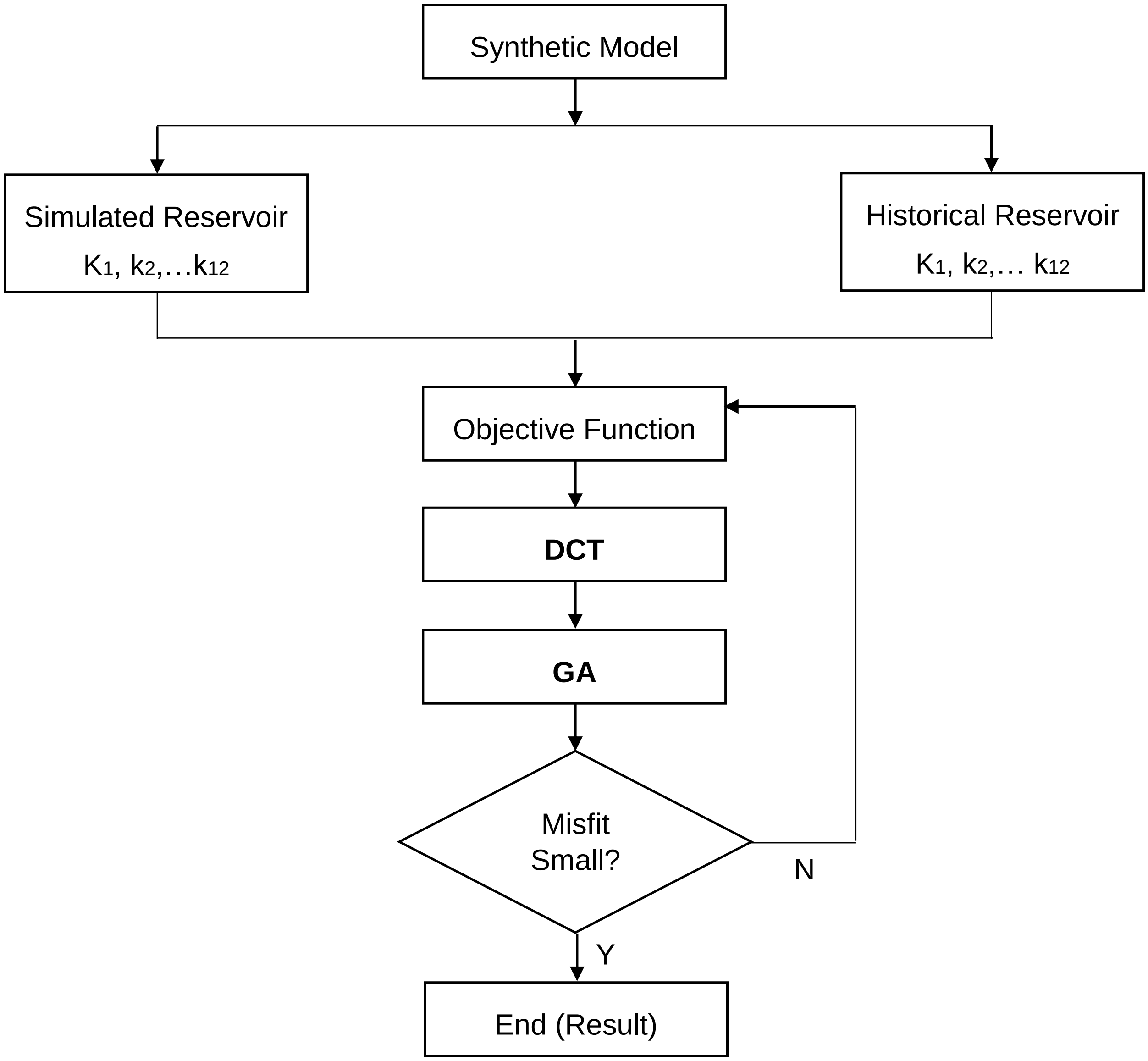

Figure 8: Project Flowchart

The above flow chart shows the processes that need to be followed to achieve the objective of this project. Initially, a synthetic reservoir model was built before obtaining the historical data and the simulated data. The simulated data was obtained by modifying the value of the permeability of the historical data. The next step was to design the objective function, which was based on the forward model. Then, Discrete Cosine Transform (DCT) algorithm was applied before optimizing the reduced parameters with Genetic Algorithm.

`

If the threshold between the simulated and the historical data is small, therefore the objective of the project, which is to produce the smallest difference between the two data, is achieved. Otherwise, more iteration(s) need to be done by modifying the objective function.

Discrete Cosine Transform (DCT)

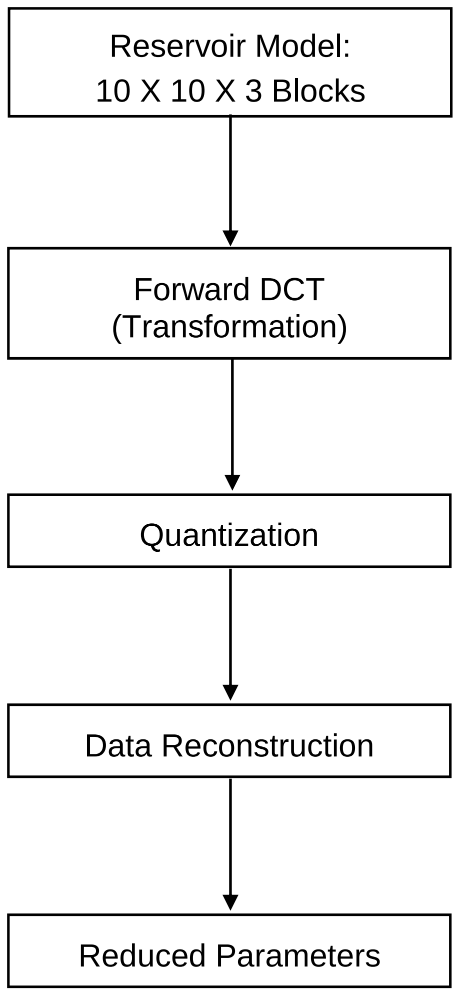

Figure 9: DCT Flowchart

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Discrete Cosine Transform can be formulated using the below equation:

$$D\ (i,j) = \frac{1}{\sqrt{2N}} C(i)C(j) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} p(x,y) \cos\left[\frac{(2x+1)i\pi}{16}\right] \cos\left[\frac{(2y+1)j\pi}{16}\right]$$

$$C(u) = \begin{Bmatrix} \frac{1}{\sqrt{2}}\ if\ u = 0 \\ 1\ if\ u > 0 \end{Bmatrix}$$

To apply the above formula, the matrix of the gridblock parameter must be known by applying this formula:

$$T_{i,j} = \begin{Bmatrix} \frac{1}{\sqrt{N}} & if\ i = 0 \\ \sqrt{\frac{2}{N}} cos\left[\frac{(2j+1)i\pi}{2N}\right] & if\ i > 0 \end{Bmatrix}$$

DCT can only work on certain value, thus the parameter value need to be subtracted with certain value to make it work and matrix M was obtain. Then DCT can be applied by multiplying matrix M with matrix T and transpose of matrix T.

$$D = TMT'$$

After that, the D matrix was multiplied with the quantization matrix which is selected based on the values of parameters which need to be eliminated. The higher the quantization number, the higher the range of parameter values which were eliminated.

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Genetic Algorithm (GA)

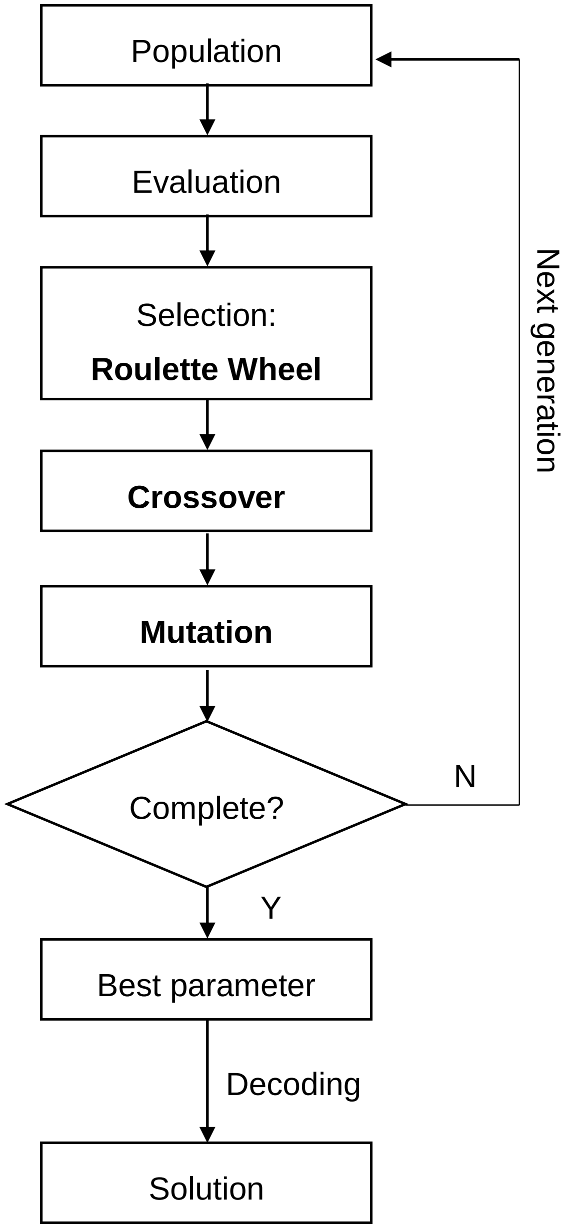

Figure 10: GA Flow Chart

The result of the history matching was obtained after genetic algorithm was applied onto the objective function. It is known that genetic algorithm works based on the probabilistic principle as the result obtained is different for each simulation. Therefore, the result is chosen based on the least iteration number f or each simulation run. The best fit for the historical data and simulated data is achieved after 93 iterations runs. 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.

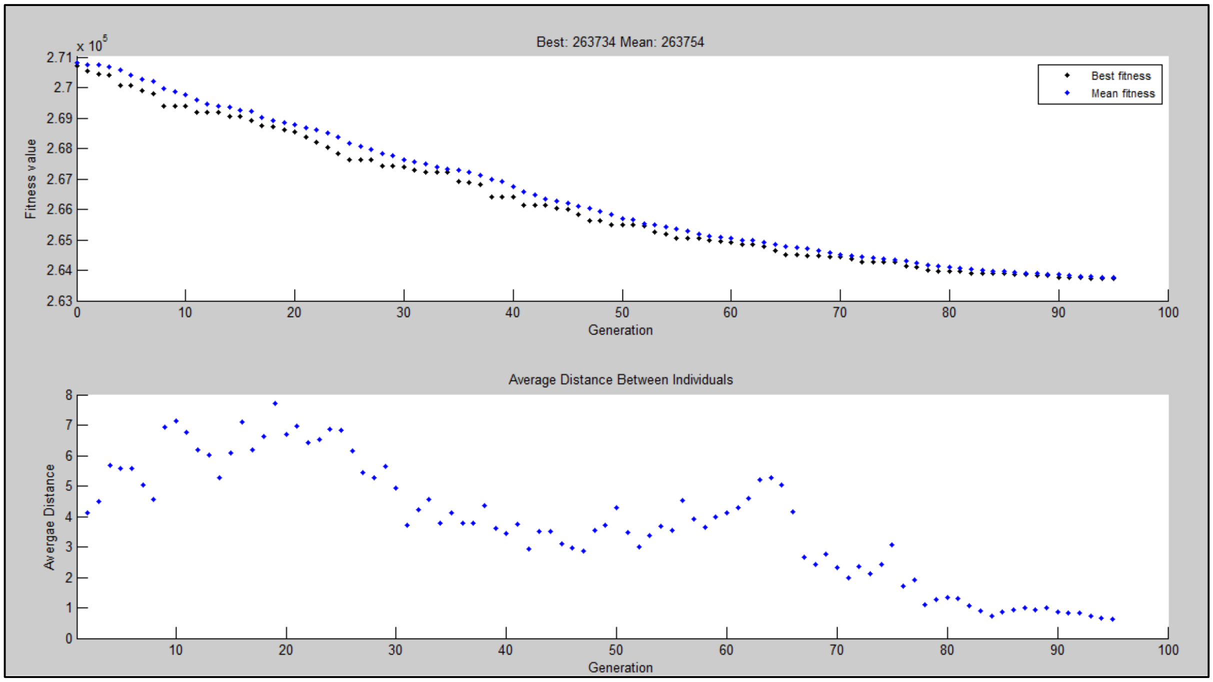

Figure 11: The Fitness value and Average Distance vs. Generation curve of the objective function

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CHAPTER 7
CONCLUSION AND RECOMMENDATION

In the nutshell, this project is a success following its successful attempt to prove the relevancy of the usage of GA and DCT combination in solving history matching problems. Apart from that, future studies can also be referenced from this project as it has produced thorough step-by-step procedures and result.

In my humble opinion, GA and DCT can be further applied onto history matching problems as it is proven to be a good combination method in solving them. They can also be used to estimate other parameter such as saturation, porosity and pressure. However, it is vital that the best value for mutation rate, crossover rate, generation number, and population size to be chosen to be applied onto the model. Otherwise, the convergence to local minimum phase might get affected throughout the process. For DCT on the other hand, the Quantization phase is very critical since that is where the less significant parameters were discarded. Hence, it is important that the quantizer calculated is optimum to keeping the more important parameters survived.

Among the recommendations that I can suggest to improve this project are:

- Other reservoir parameters to be used as well (such as oil/water saturation, porosity, reservoir pressure) in the GA and DCT combination method for better result accuracy.
- Apply the combination methods on a larger scale, especially in Malaysia, for both fundamental and business purposes.

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REFERENCES

1. Xavier, C.R., et al., *Genetic Algorithm for the History Matching Problem.* Procedia Computer Science, 2013. 18(0): p. 946-955.
2. Rwechungura, R.W., M. Dadashpour, and J. Kleppe, *Advanced History Matching Techniques Reviewed*, Society of Petroleum Engineers.
3. Cancelliere, M., F. Verga, and D. Viberti, *Benefits and Limitations of Assisted History Matching*, Society of Petroleum Engineers.
4. Walker, G.J., et al., *Assisted History Matching as a Useful Business Tool: An Example from Trinidad*, Society of Petroleum Engineers.
5. Schaaf, T., B. Coureaud, and N. Labat, *Using Experimental Designs, Assisted History Matching Tools and Bayesian Framework to get Probabilistic Production Forecasts*, Society of Petroleum Engineers.
6. Cancelliere, M., D. Viberti, and F. Verga, *Assisted history matching for petroleum reservoirs in the social computing era.* American Journal of Applied Sciences 2013. 10: p. 901-916.
7. Cullick, A.S., W.D. Johnson, and G. Shi, *Improved and More Rapid History Matching With a Nonlinear Proxy and Global Optimization*, Society of Petroleum Engineers.
8. Hermawanto, D., *Genetic Algorithm for Solving Simple Mathematic Equality Problem.* CoRR, 2013.
9. William E. Brigham, A.R.K., Louis M. Castanier, *Supri Heavy Oil Research Program*, in *U.S. Department of Energy*1998, Stanford University: Oklahoma.
10. Maucec, M., et al., *Engineering Workflow for Probabilistic Assisted History Matching and Production Forecating: Application to a Middle East Carbonate Reservoir*, Society of Petroleum Engineers.
11. Jafarpour, B. and D. McLaughlin, History Matching with an Ensemble Kalman Filter and Discrete Cosine Parameterization, 2010, Society of Petroleum Engineers.
12. Jafarpour, B. and D. McLaughlin, Efficient Permeability Parameterization With the Discrete Cosine Transform, 2007, Society of Petroleum Engineers.
13. Ken Cabeen, P.G., Image Compression and The Discrete Cosine Transform. 1994.
14. Cardoso, M.A., Data_partitioning Technique for Gradient Based Optimization Methods in History Matching. History Matching and Forecasting, 2011.
15. Cheng, H., K. Dehghani, and T.C. Billiter, A Structured Approach for Probabilistic-Assisted History Matching Using Evolutionary Algorithms: Tengiz Field Applications, Society of Petroleum Engineers

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APPENDIX

NOMENCLATURE:

P= Pressure

T= transmibility

λ=mobility

Q= flow rate

A=area

K=permeability

Kro=relative permeability to oil

μ=viscosity

Φ=porosity

B=formation volume factor

C= compressibility

T=time

Pcow=capillary pressure of oil to water

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Key Milestone

FYP 1 (January – April 2014):

Week 9 : Proposal defense (presentation)

Week 10 : Gather well information & data (for conceptual model).

Week 11 : Conceptual model building.

Week 13 : Forward model development.

Week 14 : Interim report submission.

FYP 2 (May – September 2014):

Week 3 : Application of DCT onto parameters.

Week 6 : Design Objective Function.

Week 9 : Application of GA & DCT onto parameters & code writing.

Week 12 : Draw graph & calculate the difference between the stimulated data and the historical data.

Week 13 : Final presentation (viva).

Week 14 : Final report documentation.

Final Year Project 1 (January – April 2014)

Table 1: Gantt Chart FYP 1

Activities	Week													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
• Do extensive study on topic/project. • Summarize research papers/journals. • Literature review on topic.														
• Proposal defense.														
• Build conceptual model														
• Develop forward model. • Create objective function														
• Report to supervisor (progress & result) • Interim report														

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Final Year Project 2 (May – September 2014)

Table 2: Gantt Chart FYP 2

Activities	Week													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
• Do more research on GA & DCT. • Summarize journals/research papers. • Write literature review.														
• Demonstrate DCT & GA														
• Design objective function														
• Apply DCT & GA onto problem/data.														
• Draw graph. • Calculate the difference (threshold) • Repeat step if threshold is higher than threshold value set														
• Final presentation (viva)														
• Report to supervisor (progress & result) • Final report														