# Optimization of Vertical Well Placement for Oil Field Development Based on Basic Reservoir Rock Properties using a Genetic Algorithm

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**Abstract.** Comparing the quality of basic reservoir rock properties is a common practice to locate new infill or development wells for optimizing oil field development using reservoir simulation. The conventional technique employs a manual trial-and-error process to find new well locations, which proves to be time-consuming, especially for large fields. Concerning this practical matter, an alternative in the form of a robust technique is introduced in order to reduce time and effort in finding new well locations capable of producing the highest oil recovery. The objective of this research was to apply a genetic algorithm (GA) for determining well locations using reservoir simulation, in order to avoid the conventional manual trial-and-error method. This GA involved the basic rock properties, *i.e.* porosity, permeability, and oil saturation, of each grid block obtained from a reservoir simulation model, to which a newly generated fitness function was applied, formulated by translating common engineering practice in reservoir simulation into a mathematical equation and then into a computer program. The maximum fitness value indicates the best grid location for a new well. In order to validate the proposed GA method and evaluate the performance of the program, two fields with different production profile characteristics were used, fields X and Y. The proposed method proved to be a robust and accurate method to find the best new well locations for oil field development. The key to the success of the proposed GA method lies in the formulation of the objective functions.

**Keywords:** *fitness function; field development; Genetic Algorithm; objective function; optimization; reservoir simulation; vertical well placement; well locations.*

## 1 Introduction

The development of an oil field requires a reservoir model to find the best new infill well locations in order to maximize oil recovery. The conventional technique for determining well locations is conducted manually and uses a trial-and-error process, estimating the remaining oil saturation and reservoir rock

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characteristics. Obviously, this process is time-consuming and cannot guarantee the best results, especially for large-size fields or for compositional reservoir simulation models, such as condensate gas fields. Therefore, it is essential to find a method that is much faster and sufficiently accurate.

The genetic algorithm (GA) approach is a common method in mathematical research [1-3] for solving complex optimization problems, and has been applied in petroleum engineering for reservoir development [4], well-placement optimization [5-6], reservoir characterization [7-8], and geophysics [9] studies from the years 1997 to 2004. Basically, it is a random search method founded on the mechanism of natural evolution to determine the optimum solution to complex problems. The process involves the selection, crossover and mutation of a gene that, in this case, is a product of an objective function [1-3]. Therefore, the algorithm needs an objective function in order to solve the optimization problem; the more appropriate the objective function, the more accurate the results will be.

The objective of this research was to implement a GA method in order to avoid the conventional trial-and-error process in reservoir simulation for determining optimal placement of infill wells to maximize oil field recovery. The very important first step was an investigation of the selected objective functions. This step was conducted by translating common reservoir simulation practice in petroleum engineering, *i.e.* the trial-and-error technique for selecting the well locations expected to have the best oil production in the future, using basic reservoir properties maps. This procedure was represented as an algorithm and coded into a computer program. After several logical attempts using the basic reservoir properties formulation, objective functions were introduced for the generated GA. Thus, a computer program was developed employing three basic reservoir properties, *i.e.* oil saturation, porosity and permeability, as the objective functions.

Production performance of well placement obtained by the generated GA was validated by applying the predicted well locations into a reservoir simulator of two reservoirs, fields X and Y. The results of the validation prove that the proposed method is robust and sufficiently accurate. The benefit of using this method is that there is no need to run a reservoir simulator in order to find the best well locations by assuming various scenarios. Therefore, this new approach will reduce computation time, working hours, and of course, costs.

## 2 Research Methodology

The proposed GA method is depicted in the following methodology flow chart (Figure 1). A reservoir model developed through combining the available geological model with a set of reservoir data was employed as input for the proposed GA method.

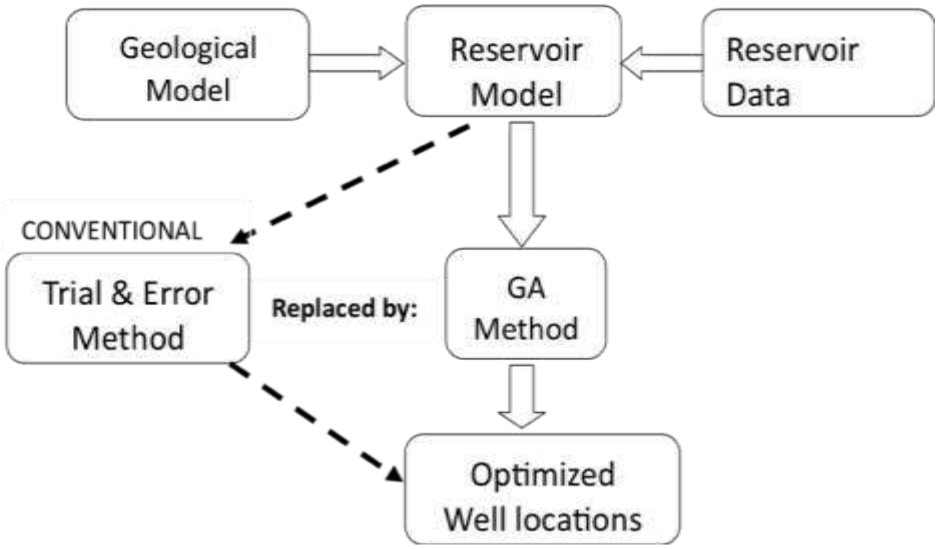


**Figure 1** Research methodology of this study: replacing the conventional trial-and-error method by a genetic algorithm method.

## 3 Field Descriptions for Reservoir Modeling Input

A reservoir simulation using a commercial finite-difference reservoir simulator requires a set of reservoir data, a geological model, reservoir fluid properties, a rock properties model, and a driving mechanism.

Two fields, namely X and Y, were used to evaluate the performance of the proposed GA. The X field is discussed in more detail than the Y field, since the X field was used to evaluate the proposed objective functions and performance of the GA, while the Y field was used only for further validation of the GA.

Fields X and Y had a similar geological depositional environment. However, the X field was relatively small and was still in its early development, whereas the Y field was relatively large and was a mature field. Thus, the profile characteristics that differentiate both fields are that the latter is in a stage of declining production, has poorer reservoir rock properties and does not have as many faults as the previous field does. Thus, the oil saturation profiles of both fields should have significantly different characteristics. Figure 2 shows the Y field in a three-dimensional map, constructed using [10]. It has a top depth structure that consists of several small anticlines, indicating a big field with many production wells. The depth structure map was put into the reservoir simulator using reference [10], and the reservoir was divided into grid blocks.

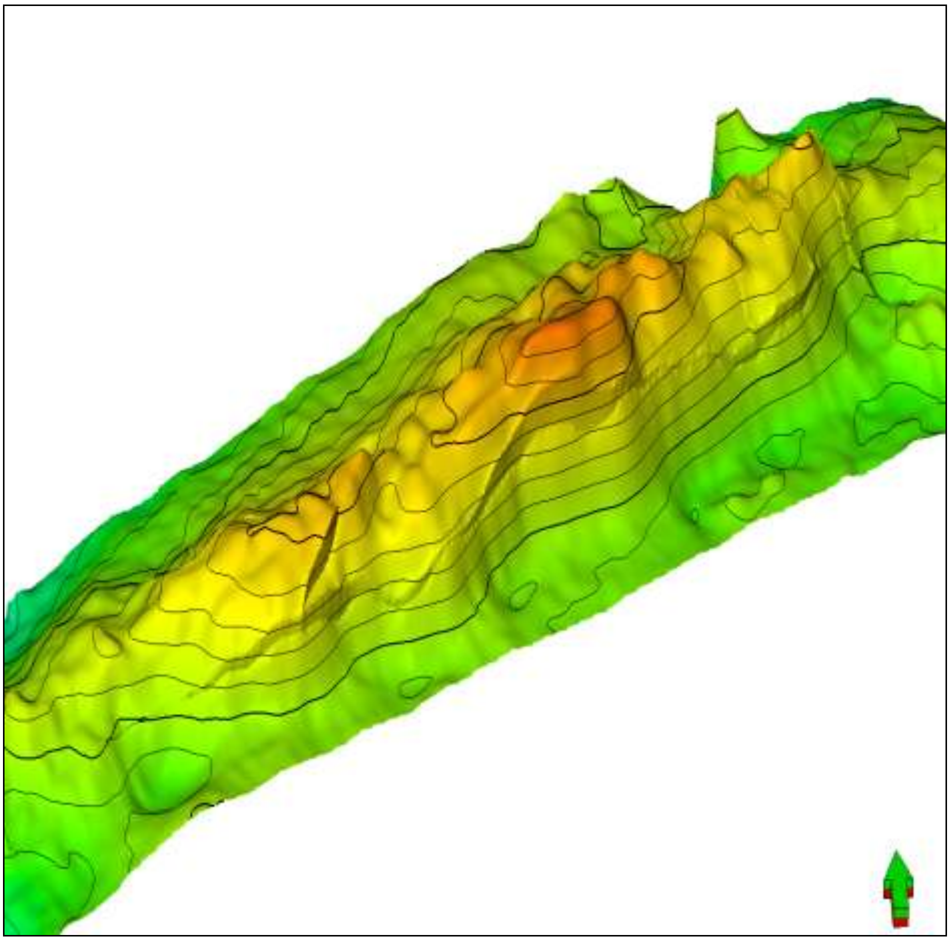

**Figure 2** Three-dimensional map of top depth structure of field Y.

Also, petrophysical properties that were obtained from well logs and reservoir core sample analyses were required for the development of the reservoir model. For example, the X field consisted of six reservoir zones, namely (from top to bottom) L-1, L-2, L-3, L-4, L-5 and L-6, as depicted in Figure 3. This is a typical well log, indicating that the L3 zone had a better quality due to its higher porosity and oil saturation (low water saturation).

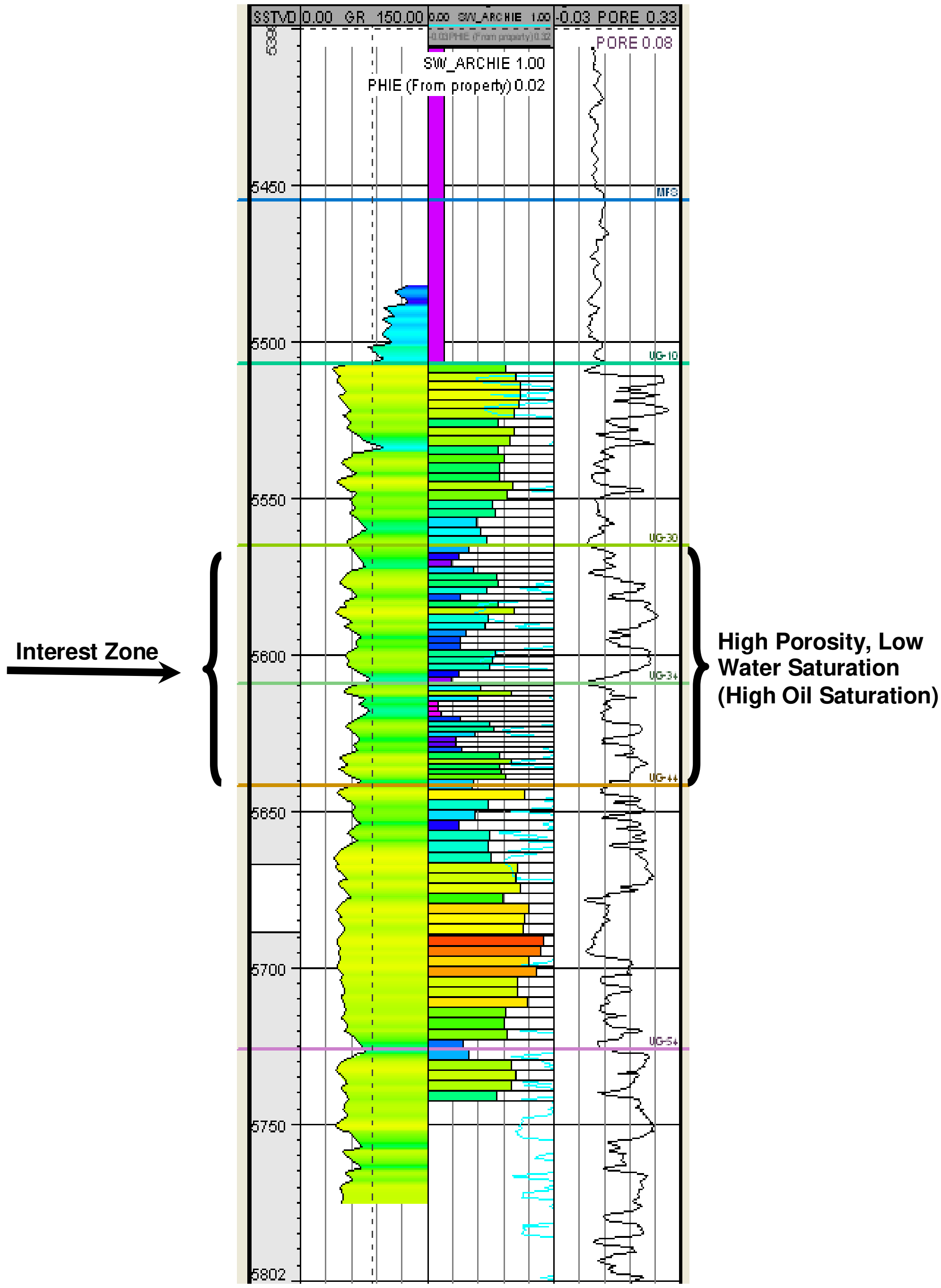


**Figure 3** Typical well logs of field X.

### 3.1 Fluid Properties of Field X

The initial reservoir pressure was 2440 psi, with bubble point pressure ranging from 1901 to 2097 psi. The oil gravity in this field was 32$^{o}$ API, with viscosity 0.94 cp and an oil formation volume factor (FVF) of 1.325 Bbl/STB. It can be concluded that the reservoir fluid type was black oil. In this field, there were two exploration wells, X-2 and X-7. From tests on the X-2 well it was found that in the initial reservoir conditions, significant oil production was present in several layers (L-1, L-2, L-3, and L-4).

### 3.2 Property Model of Field X

The sequential Gaussian simulation (SGS) distribution method was used to distribute the reservoir properties, *i.e.* porosity, permeability, and water saturation (or oil saturation), for all grids. The average porosity and permeability of field X were 12% and 147mD, respectively. Figure 4, 5, 6 show the results of using a simulator [11] that describes porosity, water saturation and permeability distributions, respectively.

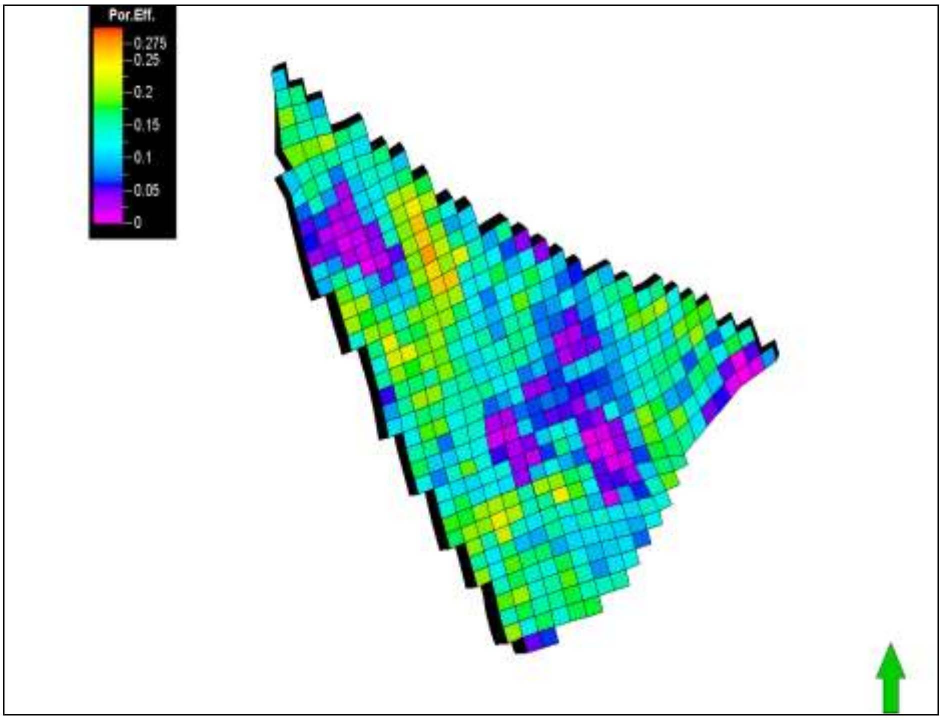


**Figure 4** Porosity distribution of the interest zone in field X.

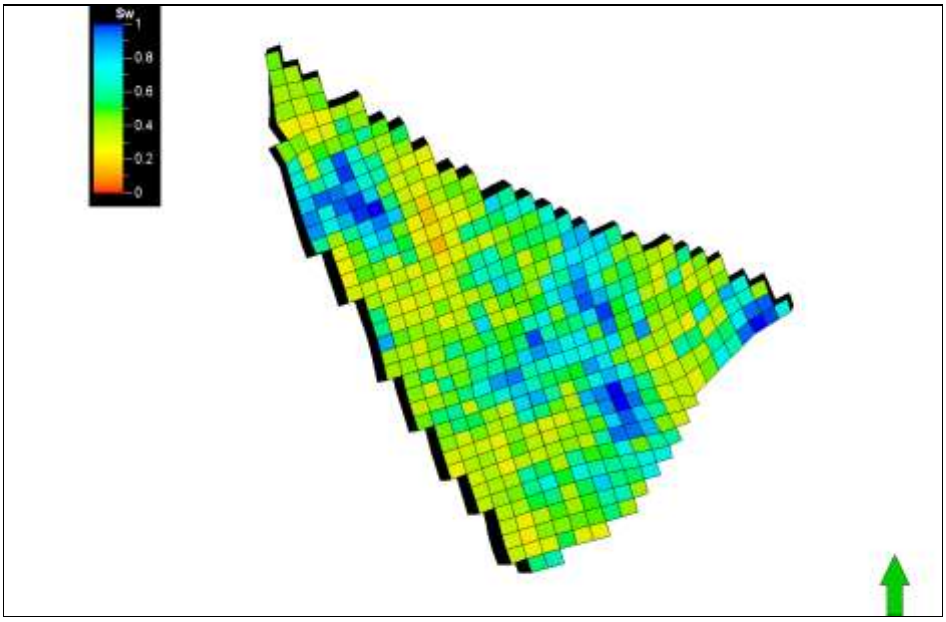


**Figure 5** Water saturation distribution of the interest zone in field X.

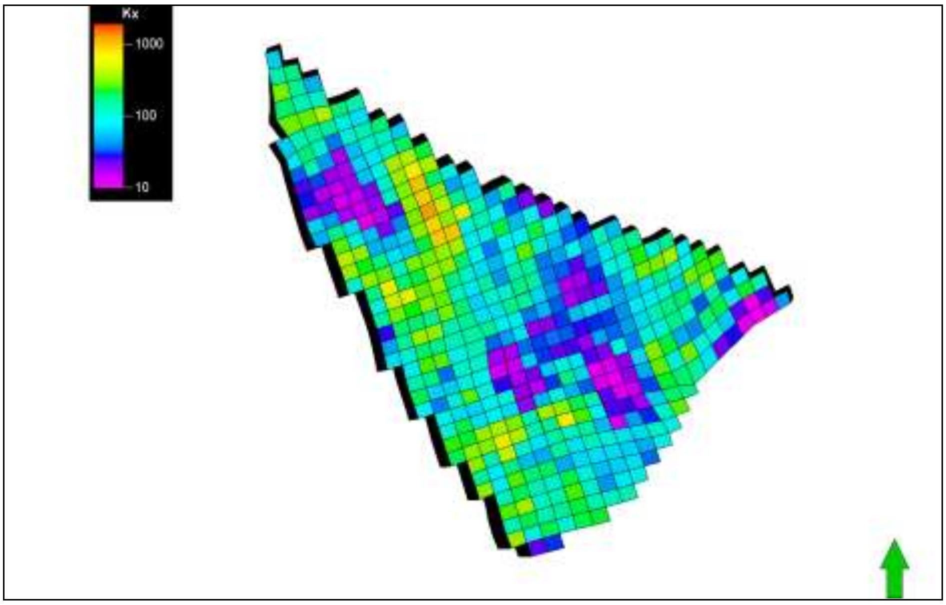


**Figure 6** Permeability distribution of the interest zone in field X.

## 4 Reservoir Simulation Model of Field X

This study focuses on zone L-2, which contained the highest level of hydrocarbon. Consequently, other layers were deliberately not included. In this model a corner-point grid was applied and a black-oil reservoir-fluid simulator was used. The reservoir model of this field was scaled up into 28 x 39 x 1 simulation grid blocks; the number of active cells was therefore 1092.

## 5 Reservoir Simulation Model of Field Y

To further validate this study, another field was examined by the proposed well-location method to find the best infill-well location, field Y. A reservoir model of this field was available, which had more than 25 development wells. The main goal of this application was to further validate the proposed selection method with a different field profile, specifically the production performance of a mature field with a large number of wells. The reservoir characteristics of field Y are not described in detail in this paper. Figures 7, 8, and 9 show the maps of porosity, water saturation and permeability distribution of this field. The figures show that there was only one small area with potentially remaining oil reserves, which created a challenge for the method to locate that area.

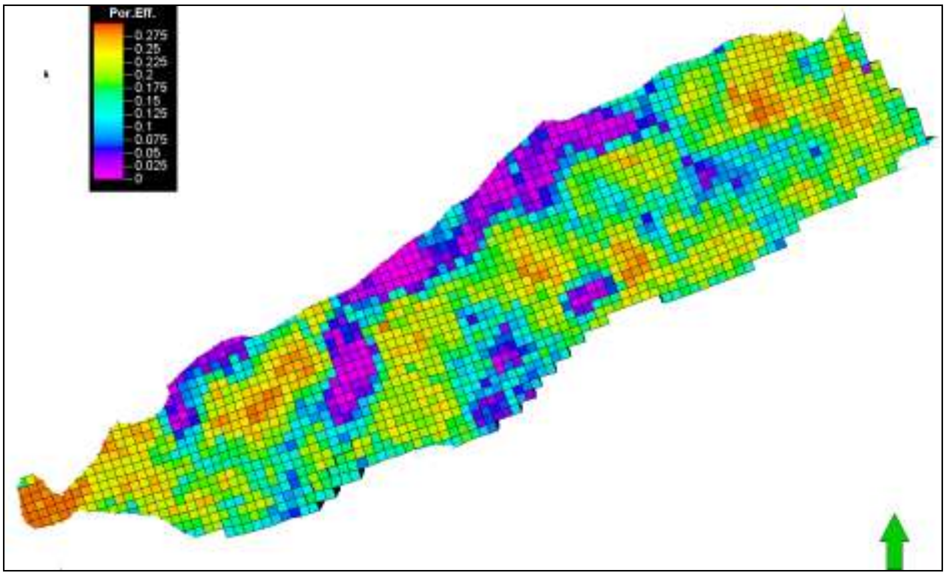


**Figure 7** Porosity distribution of the interest zone in field Y.

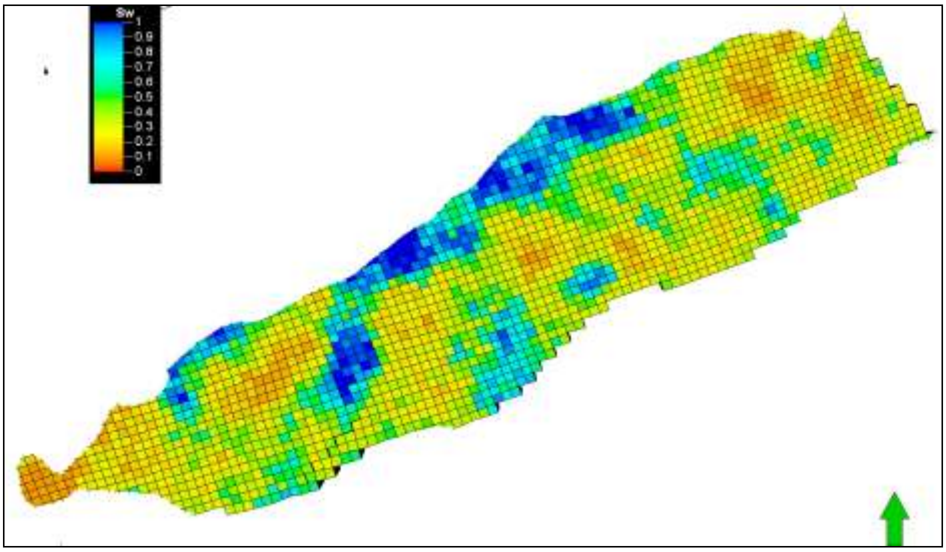


**Figure 8** Water saturation distribution of the interest zone in field Y.

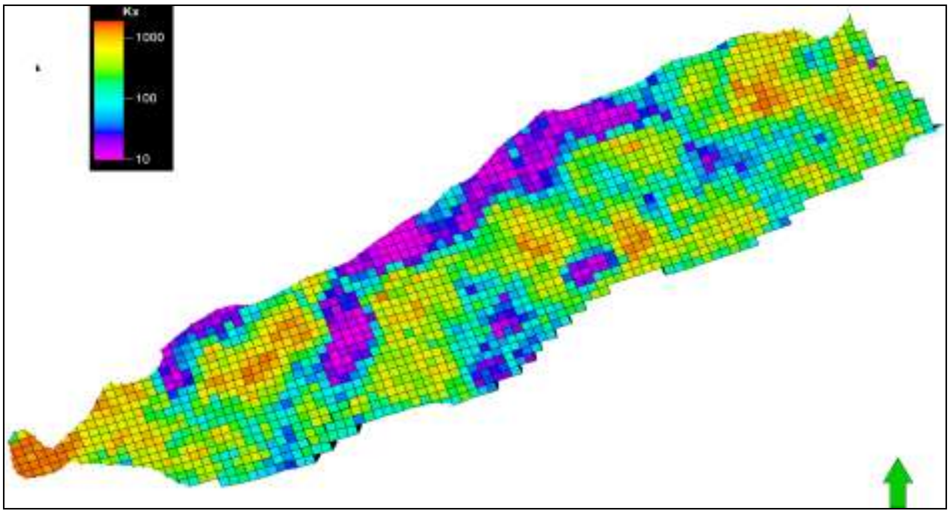


**Figure 9** Permeability distribution of the interest zone in field Y.

## 6 Genetic Algorithm Process and Application

The genetic algorithm, which was initially developed by Holland [1] in 1968, is a computer-based process with a random search technique that was inspired by the Darwinian theory of natural evolution processes [2]. The main idea behind the GA method is to find a solution from the genetics of probable solutions.

The GA method can be implemented in different disciplines of knowledge, such as business, engineering and science. It is quite robust, resulting in solutions near optimum and not easily trapped in a local optimum [7]. Another advantage of this method is that it is flexible and does not require stringent requirements of differential mathematics, continuity and others. Therefore, this method is recommended when problems are too complex and too difficult to be solved by conventional techniques.

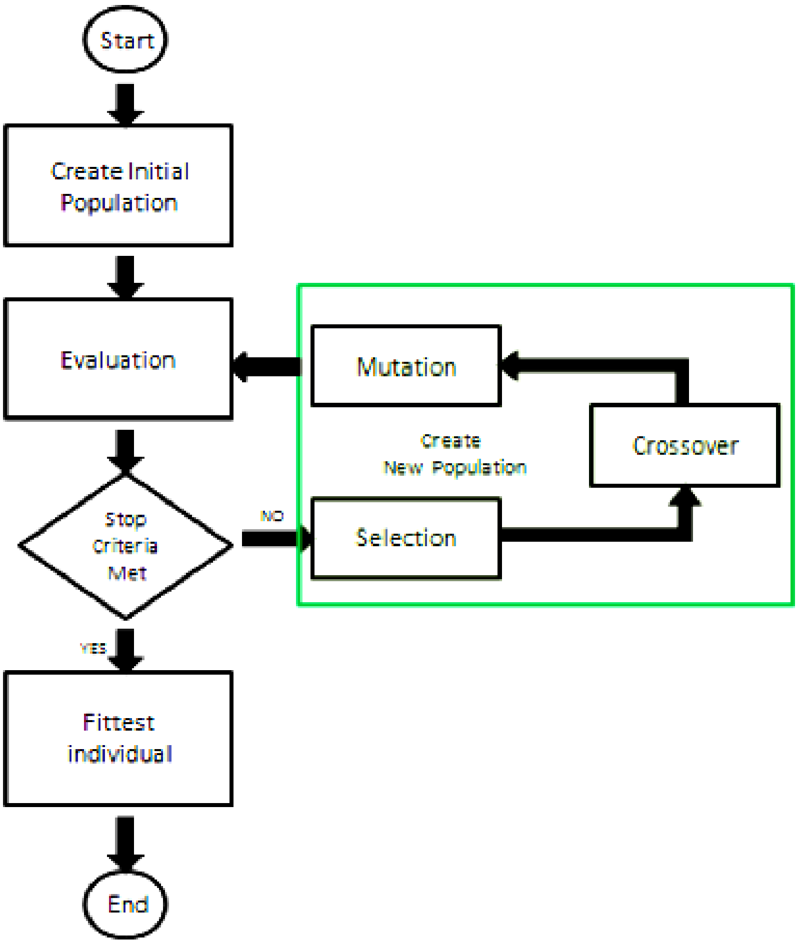


**Figure 10** Flowchart of a genetic algorithm.

The characteristics of the GA method are the following [1-2]:

1. The GA works with a coding of the parameters, but it does not directly manipulate them.
2. The GA searches not only one point as a solution to the problem, but investigates several numbers of points as possible solutions.
3. In running the GA, the presence of objective functions to solve the problem is required.
4. The realization of the GA uses probabilistic rules.

A flowchart of the GA process in simple terms is shown in Figure 10.

Following the above flowchart, the GA model used in this research is as follows:

1. Representation of the population. It is known that the desired solution is the location represented by $(x,y)$ coordinates.
2. The length of the binary variable of the population is determined by the *bit_var* parameter given by the user.
3. The operators of selection, crossover and mutation. These operators are used to get a new population, representing promising well locations. In this research, the model used the basic rules of selection, crossover and mutation.
4. The determination of fitness function that represents the objective function.

To explain the GA model briefly, we give the following example. The first step is to determine values for crossover probability, mutation probability and population size, *i.e.*, 0.85, 0.01 and 10, respectively. Then, an initial population is generated using random binary numbers as depicted in Figure 11(a), which shows the initial population of well locations in a binary representation of X and Y coordinates. This initial population is then evaluated by calculating the fitness values with the developed fitness function. The maximum value of the fitness function is the optimal solution. In order to find this optimum, evolution operators (selection, crossover and mutation) are applied to obtain a better quality of the new population. Figures 11(b) and (c) show the examples of the crossover and mutation processes.

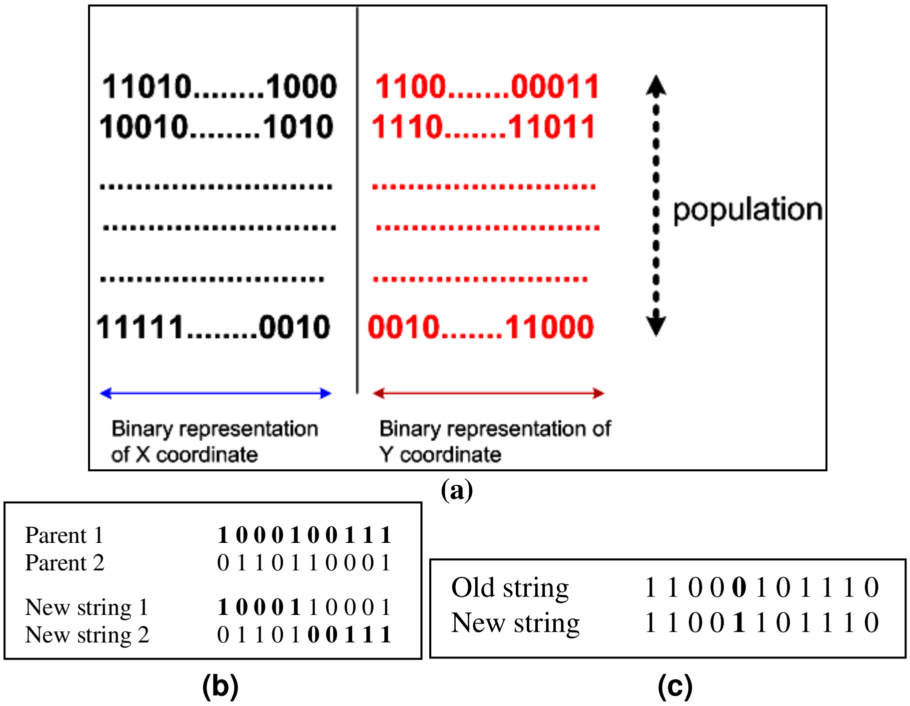


**Figure 11** (a) Binary representation of well location. (b) Illustration of crossover. (c) Illustration of mutation.

## 7 Objective-Function Development

The locations of the development and/or infill wells in the oil reservoir model are selected on the basis of the values of oil saturation/water saturation, permeability and porosity of rock at a particular grid block, and oil and water viscosity and the distribution of rock properties and saturation in adjoining grid blocks. Porosity and oil saturation represent the amount of hydrocarbon in the reservoir, while permeability represents the ability of fluid to flow through porous media. These parameters represent the well productivity. The grid block where the well will be located should have a good flow potential, supported by the same parameters in the adjoining grid blocks, in i, j, k directions. These adjoining grid blocks will form the drainage area of the well, therefore, if the values of these parameters in the adjoining grid blocks are maximal, well productivity will be high. In this research, these parameter values are presented as a function that consists of the amount of oil in the grid block (porosity, oil saturation, and grid block thickness), oil mobility (permeability and viscosity of oil), and pressure gradient. Basically, a single representation of each grid block can show its productivity value if the dynamic parameter of differential pressure is included. However, this study was based on a static quantitative representation of each grid block, which we call the fitness function. Based on its definition, the grid block to be selected as the location of the well should have the maximal fitness value. The fitness function indicates whether an individual from a population has good quality or not. For practicality, the individuals in this study were the reservoir simulation grid blocks; their three most important basic reservoir properties (porosity, oil saturation and permeability) were used as variables in the objective function. As a logical consequence, in the selection process the amount of hydrocarbon had a higher level of priority than the permeability.

As a consequence, two sequential objective functions were proposed for this study. The first one was to classify candidate grids based on their porosity and saturation, represented as:

$$Classification\ of\ grids = \left\{ \begin{array}{l} D_A = \{(x,y) \in D : f(g(x,y),h(x,y)) \in [0.4,1]\} \\ D_B = \{(x,y) \in D : f(g(x,y),h(x,y)) \in [0.2,0.4]\} \\ D_C = \{(x,y) \in D : f(g(x,y),h(x,y)) \in [0.1,0.2]\} \\ D_D = \{(x,y) \in D : f(g(x,y),h(x,y)) \in [0,0.1]\} \end{array} \right\}$$

with

$$f(g(x,y),h(x,y)) = g(x,y) * h(x,y) \tag{1}$$

where $D$ is the domain representing the reservoir grid, $f$ is a function of the combined values of porosity and saturation in a particular grid block, $g(x,y)$ is the porosity value on $x,y$ coordinates, and $h(x,y)$ is the saturation value on $x,y$ coordinates.

The next step was based on the evaluation of the drainage radius. A reservoir system involves a dynamic process of fluid-flow from reservoir to well bore, thus, the surrounding grids of a well contribute to the well's production. In the GA computer program using the abovementioned objective functions, the problem was to quantify the contribution of fluid-flow in the surrounding grid blocks to the well's production. It is obvious that the closer a grid block is located to the well, the larger will be its contribution to the well's production. The assumed drainage area was taken into consideration in the objective-function calculation called radius of evaluation R, using the properties of the grid blocks surrounding the production well. The formulation of this objective function is as follows:

$$\max_{(x,y)\in R} F(g(x,y),h(x,y),i(x,y)) = \overline{g(x,y)} * \overline{h(x,y)} * \overline{i(x,y)} \tag{2}$$

where $\overline{g(x,y)}$ is the average of the porosity value on $x$,$y$ coordinate, $\overline{h(x,y)}$ is the average of the saturation value on $x$,$y$ coordinate, $\overline{i(x,y)}$ is the average of the permeability value on $x$,$y$ coordinate.

In this research, alternative well locations could also result from sorting the best individuals based on fitness-function values and then considering the euclidean distance from each other.

It has been mentioned that in the GA application, the radius of evaluation should be determined and evaluated. For field X, it was proven that when R=0, it gave the best solution. Using the same procedure, it was found that R=1 gave the best solution for field Y.

## 8 Results and Discussion

To evaluate the performance of the proposed GA, results of its application were compared with results of a conventional manual well-location selection method. Two scenarios were investigated, *i.e.* a one-well scenario and a three-wells scenario. Both scenarios were set with the same constraints as on objective function evaluation, and all wells were opened simultaneously.

### 8.1 Conventional Manual Trial-and-Error Reservoir Simulation Results

In a conventional manual reservoir simulation, a trial-and-error process of selecting the best grid block locations is conducted by iteratively considering the three basic reservoir properties (porosity, oil saturation, and permeability) running a one-by-one reservoir simulation at the chosen locations. Logically, the best location is where the highest values of these three properties occur at the same place, even though finding this location with the conventional method is almost impossible or unrealistic, especially for a large field. Nevertheless, for this considerably sized field the resulting best grid locations were ranked. We also present the results of a multiple-wells scenario, for which a drainage radius was considered. As a rule of thumb it was assumed to be 2 neighboring grid blocks. A radius of evaluation equal to zero (R=0) means that the drainage radius consisted of the well grid block only; R=1 means that a radius of one grid block surrounding the well grid block was considered, and R=2 means a radius of two grid blocks was considered.

Table 1 and 2 describe well locations and oil recovery for field X resulting from the conventional trial-and-error method, compared to the results of the previous reservoir simulation, for the one-well scenario and the three-wells scenario, respectively.

**Table 1** The one-well scenario for field X, with R = 0.

| Location | | Oil Recovery | Recovery Factor | Δ RF with Res. Simulation |
|---|---|---|---|---|
| X | Y | (STB) | (%) | (%) |
| 7 | 27 | 2891840.5 | 17.94 | 0 |

**Table 2** The three-wells scenario for field X, with R = 0.

| Location | | Oil Recovery | Recovery Factor | Δ RF with Res. Simulation |
|---|---|---|---|---|
| X | Y | (STB) | (%) | (%) |
| 7 | 27 | 3521585 | 21.85 | 0.15 |
| 18 | 24 | | | |
| 9 | 27 | | | |

Δ RF with reservoir simulation: differences with respect to the previous reservoir simulation results.

Tables 3 and 4 describe the well locations and oil recovery for field Y, for the one-well scenario and three-wells scenario, respectively.

**Table 3** The one-well scenario for field Y, with R = 0.

| Location | | Oil Recovery | Recovery Factor | Δ RF with Res. Simulation |
|---|---|---|---|---|
| X | Y | (STB) | (%) | (%) |
| 90 | 36 | 9825374 | 8.98 | 0.41 |

**Table 4** The three-wells scenario for field Y, with R = 0.

| Location | | Oil Recovery | Recovery Factor | Δ RF with Res. Simulation |
|---|---|---|---|---|
| X | Y | (STB) | (%) | (%) |
| 90 | 36 | 16448811 | 14.03 | 1.31 |
| 105 | 34 | | | |
| 79 | 36 | | | |

We can see that the one-well scenario gave perfect results for both fields, as shown by the small differences with the reservoir simulation results. However, the bigger field Y showed a larger difference. Moreover, the three-wells scenario yielded larger differences than the one-well scenario. This clearly shows that the more complex the problems are, *i.e.* the higher the number of wells and the larger the field, the bigger the differences are. Thus, the conventional trial-and-error method is likely to be harder and more time-consuming when trying to find the best well location when the investigated field is larger.

## 8.2 Objective-Functions Evaluation of the Proposed GA Method

The objective functions of the proposed GA method should be evaluated first with respect to avoiding local optimum solutions. Also, in order to find the proper radius of evaluation, the GA application is run for various radii.

Some statistical parameters should be properly assumed to run the GA application for this optimization problem study. Table 5 shows the suitable GA parameters for this case study. The population size means the number of grid blocks that have specific properties of porosity, permeability, and water saturation. The maximum number of iterations was set to guarantee that the maximum value of the objective function could be achieved. Crossover probability was set to 0.9 to give a high probability for the process of crossover to occur, though not equal to always happening (100%). On the other hand, setting the mutation probability to 0.01 was meant to limit mutation, so new individuals were generated mostly through a combination of individuals.

**Table 5** GA calculation parameters for the proposed GA method.

| | |
|---|---|
| **Population size** | 100 |
| **Maximum Number of iteration** | 1500 |
| **Crossover Probability** | 0.9 |
| **Mutation Probability** | 0.01 |
| **Number of variables** | 2 (x and y) |
| **Chromosome Length** | 20 for each variable |
| **Interval** | [1 - 28] for x and [1 - 39] for y |
| **Radius of evaluation** | 0, 1, 2, 3, 4 |

To check the application, the results from a number of iterations were investigated by comparing them with the proposed well locations obtained from the reservoir simulation runs. For all simulation runs, the well production time was set to 15 years, with an oil rate target of 2000 STB/day. Table 6 shows the results of some iterations for R=0. Figures 12 and 13 illustrate the relationships between number of iterations, fitness value, and oil recovery. As can be seen, the proposed well location moved from iteration to iteration, which indicates that the proposed GA method effectively searched for the best location in different places. The fitness value consistently became higher during the successive iterations of the calculation (Figure 12). The same goes for the recovery factor (Figure 13). This also means that the proposed GA method will not be trapped in a local minimum.

**Table 6** The proposed GA and reservoir simulation results for $R$ = 0.

| Iteration | Location | | Fitness Values | Porosity | Oil Saturation | Permeability (mD) | Oil Recovery (STB) |
|---|---|---|---|---|---|---|---|
| | x | y | | | | | |
| 1 | 5 | 27 | 30.096 | 0.27 | 0.817 | 270.3 | 2089725.3 |
| 5 | 5 | 27 | 30.096 | 0.27 | 0.817 | 270.3 | 2089725.3 |
| 10 | 5 | 27 | 30.096 | 0.27 | 0.817 | 270.3 | 2089725.3 |
| 100 | 7 | 28 | 30.219 | 0.32 | 0.818 | 516.1 | 2777452.3 |
| 500 | 7 | 28 | 30.219 | 0.32 | 0.818 | 516.1 | 2777452.3 |
| 900 | 7 | 28 | 30.219 | 0.32 | 0.818 | 516.1 | 2777452.3 |
| 1000 | 7 | 27 | 30.274 | 0.34 | 0.818 | 614.8 | 2891840.5 |
| 1500 | 7 | 27 | 30.274 | 0.34 | 0.818 | 614.8 | 2891840.5 |

Furthermore, the same analyses were implemented for R=1, 2, 3 and 4; the results are summarized in Table 7. These results show that the proposed GA method was not trapped in a local optimum, except for R=1. And, R=0 was the best radius of the evaluated parameters for field X, because its location gave the highest oil recovery.

**Table 7** Results of various values for $R$.

| Radius | Location | | Fitness Value - Oil Recovery Relation | Oil Recovery (STB) |
|---|---|---|---|---|
| | $x$ | $Y$ | | |
| 0 | 7 | 27 | Positive | 2891840.5 |
| 1 | 6 | 27 | Negative | 2310701.8 |
| 2 | 8 | 27 | Positive | 2418505.0 |
| 3 | 8 | 27 | Positive | 2418505.0 |
| 4 | 9 | 28 | Positive | 1881947.1 |

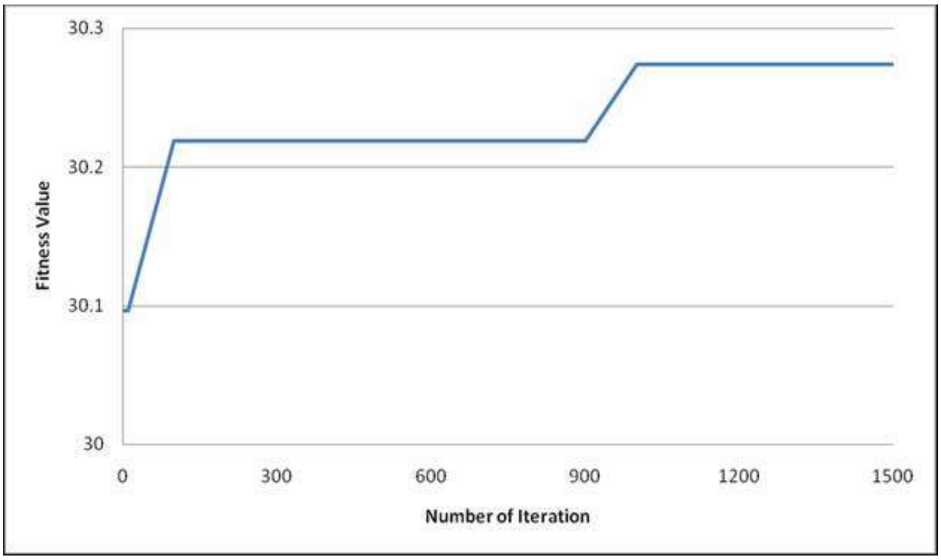


**Figure 12** Fitness function value evaluation with respect to number of iterations.

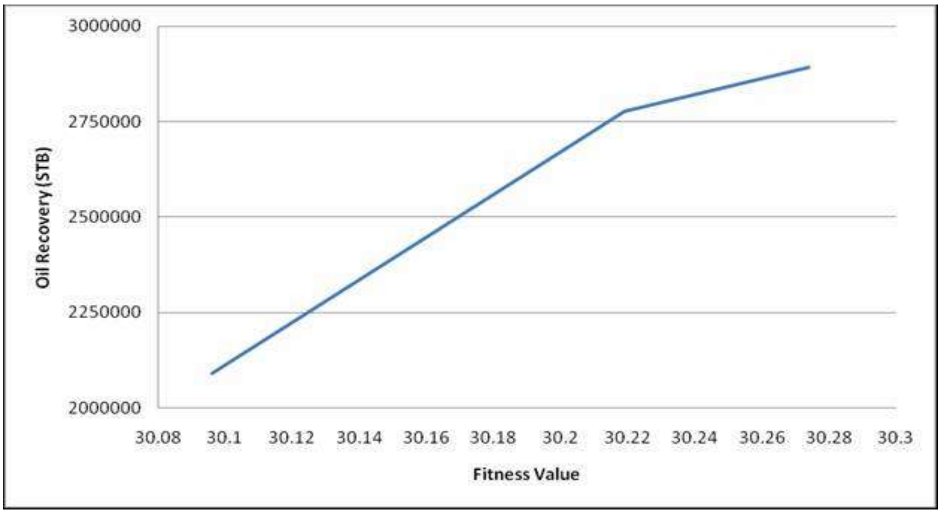


**Figure 13** Oil recovery evaluation with respect to fitness function.

### 8.3 Proposed GA Method Results

The results of the proposed GA method for both fields are described in Tables 8-11. A situation similar to the one-well scenario still gave perfect results, as shown by the small differences compared to the reservoir simulation results for both fields. However, the larger field yields a larger difference. Also, the three-wells scenario yielded larger differences than the one-well scenario. In other words, the proposed GA method, which is accurate and robust, might be able to take hurdles in more complex problems, *i.e.* when a higher number of wells and a larger field are involved. Using the conventional trial-and-error method requires hard work and plenty of time to accurately find the best well locations.

**Table 8** The one-well scenario for field X, with $R$ = 1.

| Location | | Oil Recovery | Recovery Factor | Δ RF with Res. Simulation |
|---|---|---|---|---|
| x | y | (STB) | (%) | (%) |
| 7 | 27 | 2891840.5 | 17.94 | 0 |

**Table 9** The three-wells scenario for field X, with $R$ = 1.

| Location | | Oil Recovery | Recovery Factor | Δ RF with Res. Simulation |
|---|---|---|---|---|
| x | y | (STB) | (%) | (%) |
| 7 | 27 | 3545128.3 | 22 | 0.15% |
| 18 | 25 | | | |
| 15 | 30 | | | |

**Table 10** The one-well scenario for field Y, with $R$ = 1.

| Location | | Oil Recovery | Recovery Factor | Δ RF with Res. Simulation |
|---|---|---|---|---|
| x | y | (STB) | (%) | (%) |
| 91 | 34 | 10275948 | 9.39 | 0.41 |

**Table 11** The three-wells scenario for field Y, with $R$ = 1.

| Location | | Oil Recovery | Recovery Factor | Δ RF with Res. Simulation |
|---|---|---|---|---|
| x | y | (STB) | (%) | (%) |
| 91 | 34 | 16790774 | 15.34 | 1.31 |
| 90 | 36 | | | |
| 79 | 36 | | | |

Figure 14 shows the selected well locations based on previous study results and those based on the proposed GA method.

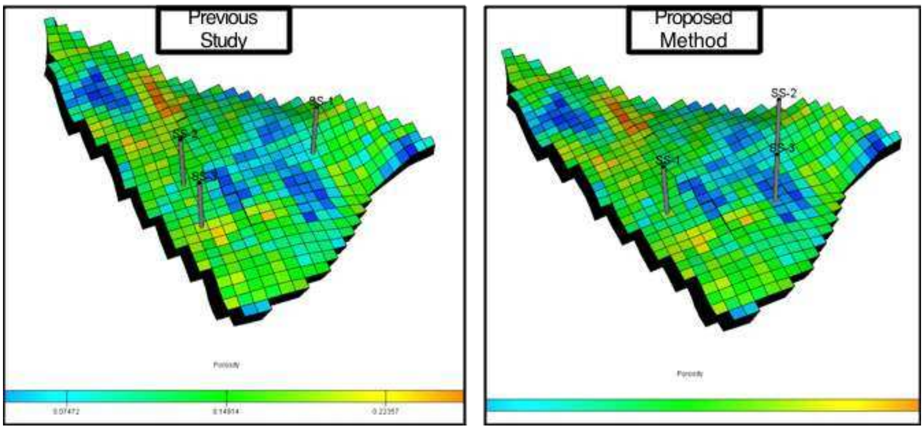


**Figure 14** Selected well locations of a previous study compared to those using the proposed GA method.

## 8.4 Discussion of the Proposed GA Calculation Procedure

In the proposed GA method, a two-step calculation procedure is introduced that employs two sequential objective functions. The first objective function is used for classifying the hydrocarbon volume and at certain values for classifying interval criteria. These assigned values are based on qualitative investigation of running experiments for the whole field, using geological software. Thus, some subjective reservoir engineering judgments are embedded in the first objective function.

The proposed GA needed statistical parameters that had to be set properly in order to make sure the algorithm calculation process worked well. The maximum number of iterations was set to a certain number so that the calculation of the objective function reached the maximum value as the iteration proceeded; it did not produce significantly higher values. The crossover probability was set to a relatively high value, *i.e.* 0.9, in order to make the algorithm permissive towards the occurrence of crossover. On the other hand, the mutation probability was set to a small value, *i.e.* 0.01, to limit the number of mutations. These conditions were intended to yield more heterogeneous individuals, since crossover allows a new individual to be generated from combustion among individuals, whereas mutation allows a new individual to be generated from the individual itself.

The proposed GA method proved to be a robust way of finding the best well location, as shown by its capability to yield better oil production performance results than the conventional reservoir simulation methods for both studied fields, X and Y. For the simple problem of a one-well scenario for field X, the proposed GA method gave the same result as the conventional method. For the three-well scenario, the GA method could give at least the same or even better well locations by producing a 0.15% higher oil recovery compared to the conventional method. Furthermore, in the case of field Y, the proposed method also gave better well locations for both the one-well and the three-wells scenario, by producing higher oil recoveries, 0.41% and 1.31% higher respectively, compared to the conventional method.

The proposed GA also involved the contribution of surrounding grid blocks for determining well locations. However, defining the radius of evaluation that determines the number and position of neighboring grid blocks needs further study, since the radius of evaluation still affects the well production set manually; the heterogeneity of the reservoir influenced the setting. Nevertheless, this simplification was powerful, since the proposed GA was able to give good results for well location selection.

## 9 Conclusions

The proposed GA method is proven to be a robust and accurate method to help find the best well locations for oil field development by employing three static reservoir rock parameters, *i.e.* porosity, permeability, and saturation, which are also used in conventional reservoir simulation practice. This method avoids the time-consuming reservoir simulation process in searching the best field development scenario by running various future performance scenarios using the conventional, trial-and-error reservoir simulation method, especially when large-size fields or condensate gas fields are involved that need compositional simulators.

The key for success of the proposed GA method mainly lies in the formulation of the objective functions, which requires skill and experience with oil field development best practices using reservoir simulation and the ability to transform those skills into a GA formulation in order to fulfill the objective functions and solve the problem.

The inclusion of a radius of evaluation in the proposed GA method gave more realistic results in locating the best development-well locations. However, the radius of evaluation function needs to be studied further in order to develop an automatic determination technique.

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