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Selection of an Optimal Hybrid Water/Gas Injection Scenario for Maximization of Oil Recovery Using Genetic Algorithm

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Abstract

Production strategy from a hydrocarbon reservoir plays an important role in optimal field development in the sense of maximizing oil recovery and economic profits. To this end, self-adapting optimization algorithms are necessary due to the great number of variables and the excessive time required for exhaustive simulation runs. Thus, this paper utilizes genetic algorithm (GA), and the objective function is defined as net present value (NPV). After developing a suitable program code and coupling it with a commercial simulator, the accuracy of the code was ensured using a synthetic reservoir. Afterward, the program was applied to an Iranian southwest oil reservoir in order to attain the optimum scenario for primary and secondary production. Different hybrid water/gas injection scenarios were studied, and the type of wells, the number of wells, well coordination/location, and the flow rate (production/injection) of each well were optimized. The results from these scenarios were compared, and simultaneous water and gas (SWAG) injection was found to have the highest overall profit representing an NPV of about 28.1 billion dollars. The application of automated optimization procedures gives rise to the possibility of including additional decision variables with less time consumption, and thus pushing the scopes of optimization projects even further.

Keywords: Optimization, Production Optimization, Well Placement, Genetic Algorithm

1. Introduction

Selecting an optimum choice for the development of a hydrocarbon reservoir requires a full understanding of the variations in costs and incomes caused by changing a production scenario. The optimal development of an oil field requires the study and evaluation of many parameters, including reservoir characterization, drilling locations, and production strategy. Using common exhaustive simulations does not seem reasonable due to the large amount of information and the huge number of variables involved.

Genetic algorithm (GA) is a technique for search and optimization, which is based on genetic principles and natural selection. GA provides the opportunity for constructing a population of individuals with different characteristics, and among this population, selecting the people who are the

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fittest for the desired purpose (the ones with the least cost). This method was introduced and developed by Holland (1973) and was finally completed and published by Goldberg (1985), where GA was used for flow control in gas pipelines.

Lang and Horne (1983) considered production parameters such as gas injection rate (in gas lift operations) and downhole flowing pressure as decision parameters for maximizing oil production, through GA, with respect to the reservoir conditions and physical constrains such as the capacity of pipelines and wellhead facilities. The applications of GA in oil industry were briefly addressed by Jefferys (1993). The discussed cases, including the optimization of drilling operations, casing running operations, production planning, and the optimal method for mixing different types of crude oil in order to provide the suitable feed for refineries, etc. Moreover, the possibility of using these algorithms in such cases was examined, and the advantages and disadvantages of each algorithm were evaluated.

The pioneers of GA application in well placement optimization were Bittencourt and Horne (1997). They combined economic and simulation studies with evolutionary hybrid genetic algorithms (HGA) using polytope search. Objective functions based on net present value (NPV) coupled with HGA techniques were employed to calculate well location, well type, well number, and drilling direction (in horizontal wells) in oil and gas fields. Pan and Horne (1998) used the least squares and kriging interpolation algorithms for scheduling field development and a water injection project with the aim of reducing the number of simulations and obtaining the optimal strategy. Their results indicated a significant reduction in the number of simulations required, and they chose their final and optimal strategy by interpolating between the objective function values obtained from these simulations.

Due to the high simulation runtime required by the commercial software, Stoisits et al. (1999) decided to use artificial neural networks instead of the objective function, and used a genetic natural selection process to solve the nonlinear allocation problem. They successfully optimized the wellhead facilities, flow pipelines, and the well performance model for Kuparuk River field in northern Alaska. Güyagüler (2002) addressed data uncertainty and optimized the locations of the injection wells in Pompano oil field in the Gulf of Mexico. Through using HGA and kriging algorithm, simulation time was reduced significantly and the maximization of NPV was made possible. The outcomes were also evaluated and verified in comparison to exhaustive simulation results.

Determination of the optimal parameters of nonconventional wells was presented by Yeten et al. (2003) using GA in association with other acceleration routines. In their research, they defined an objective function consisting of NPV and attempted to optimize the type, number, location and trajectory of these wells by incorporating HGA. Furthermore, uncertainty effect was taken into account via a multiple realization approach. Badru and Kabir (2003) also conducted optimization on well positioning in water and gas injection processes using HGA with polytope algorithm as the assisting method. Their results showed that in a synthetic reservoir, horizontal wells have a higher recovery compared to vertical wells. However, in real reservoirs, the lower the parameter K_v/K_h was, the lower the marginal profit of the horizontal wells was. Xuefei and Mohanty (2003) presented a method for the proper analysis of the production history as a substitute for automatic history matching by using GA. The provided objective function was an error function consisting of the differences between the calculated and experimental values of the reservoir production. A good match was obtained for primary drainage at low injection rates.

Time-dependent information was used along with HGA in the work of Özdoğan (2004) for uncertainty reduction. In their method, the production data are obtained while the wells are being drilled, and they are taken into account for further decision-making. Therefore, unlike previous approaches, history matching gradually becomes more effective in the optimization of the well placements. Due to the presence of production data, uncertainties about the optimization are also reduced at each step of the optimization. In another work, Tavakkolian et al. (2004) introduced a novel stochastic method through which they optimized the oil and gas-condensate production systems. Their approach made it possible to achieve the optimal values for a function with a great number of decision variables in such a way that the highest amount of economic benefit could be attained. Their GA-based method first used a mathematical equation to optimize wellhead facilities; then, the results were analyzed and re-optimized to increase profitability. As the output of the program, the parameters to which the optimization was applied consisted of tubing (single or dual) size and depth, choke size, the number of separators, and the pressure of the separators.

The uncertainties associated with field development may be technical, which is related to size and quality of the reserve, or may be in accordance with market conditions. When there exists many different choices for investment, deciding on the most suitable option will be extremely difficult due to the high number of possibilities and parameters involved in the calculations. Lazo et al. (2007) attempted to optimize decision making under the conditions of market uncertainty by incorporating real option theory, Monte Carlo simulation, and genetic algorithm.

Zarei et al. (2008) utilized HGA with a neuro-fuzzy system, which acts as a proxy for the optimization process. The network is selected as the objective function, and the algorithm obtains the objective function value for various chromosomes. They performed their study using a synthetic reservoir and realized that HGA has higher reliability and speed in comparison with GA and non-proxy approaches. Nogueira and Schiozer (2009) addressed production strategy optimization using GA in two exclusive cases with only vertical and horizontal wells. After investigating the two situations, they concluded that implementing horizontal wells results in a higher NPV and specified the optimal number and location of the wells.

Bukhamsin et al. (2010) coupled continuous type GA with dynamic mutation and hill climbing technique to enhance the performance in obtaining the optimal design of the multilateral wells. Their results were applied to the development of a heterogeneous carbonate reservoir in Saudi Arabia. Moreover, the continuous GA was found to be more robust than the usual binary genetic algorithms. Morales et al. (2010) attempted to optimize the location of horizontal wells in a gas-condensate reservoir model from a northern Qatar field under several case scenarios. It was discovered that the location of horizontal wells is not a significant factor in cumulative gas production as it is in oil fields. Additionally, they noted that convergence to global maximum could be challenging due to the surrounding local maxima.

Optimization of CO_2 flooding performance in a real reservoir in the presence of financial and physical uncertainties was reported by Chen et al. (2010), where they used a modified GA along with the geostatistical technique for risk assessment and NPV maximization. Gas injection rate and flowing downhole pressure in production wells were the selected controlling variables. As a result, ultimate recovery and NPV were both increased, and the efficiency and reliability of genetic algorithm was confirmed.

In a review study, Nasrabadi et al. (2012) examined different methods of optimizing well placement and addressed the shortcomings of the existing methods in the literature. They stated that although GA produces reliable outcomes, it still requires a considerable number of simulation runs. The authors further discussed the inefficiency of the conventional finite difference techniques in commercial simulators as well as the necessity of more attention to gas reservoirs and tertiary methods of oil recovery.

Salmachi et al. (2013) constructed a framework to find the optimal placement of infill wells in coal bed methane fields. A semi-synthetic reservoir was used for this purpose. It was found that the key parameter controlling the location of infill wells and thus the profitability of the project is the cost of water treatment and disposal.

Wang et al. (2014) used a sector model to validate enhanced oil recovery (EOR) results on a field scale by using a sector model at Chevron Corporation. This sector model covers 1/6 of the field area and includes natural fractures, plant capacity limitations, complex production rules, existing sour gas injection, and high well count. Their work presents a method to model full field performance and to finally generate suitable predictions.

Seyed-Attar et al. (2015) reported that a proper field development strategy is an integrated, multi-disciplinary task mainly during gas injection scenario in asphaltenic oil reservoirs. In their study, based on the parameters obtained from the experimental studies, asphaltene precipitation and deposition are investigated by a commercial simulator. Then, after suggesting a comprehensive development plan, the effect of asphaltene deposition on fracture parameters is quantified.

At Shell, Liping Jia et al. (2015) used a sector modeling to identify and rank different aspects of CO_2 injection in an oil field with 500 wells, 70 years of historical production, and water injection.

In a recent work, Sambo et al. (2016) applied adaptive GA to an infill-drilling program. After history matching, the optimization results were compared to those of the exhaustive design of expert methods. genetic algorithm successfully maximized recovery at a significantly higher speed and proved to be a useful tool, especially when compositional simulations are required.

2. Methodology

This paper intends to address the optimization of the number and location of the wells, whether production or injection, as well as their rates, under certain scenarios by means of GA for one of Iran southwest reservoirs. In the optimization process, a connection is established between the GA optimizer engine in MATLAB and a commercial simulator for several times. The two sections are coupled and made completely compatible with each other to perform the optimization on the specified reservoir without any problem.

After ensuring the accuracy of the code using a synthetic reservoir, natural production scenario from the real reservoir is investigated. The goal is to find the optimal placement and production rate of the wells in order to increase the oil production. Later, after the initial reservoir pressure drops and the need for secondary recovery (e.g. additional injection wells) arises, we attempt to find the optimum location and injection rate for the new wells under several scenarios in order to extend the reservoir lifespan and to obtain the highest oil recovery. Ultimately, the values for NPV from different scenarios are compared, and the optimum strategy is reported. This process is illustrated in **Figure 1**. The overall procedure for the optimization in any genetic algorithms is also shown in **Figure 2**.

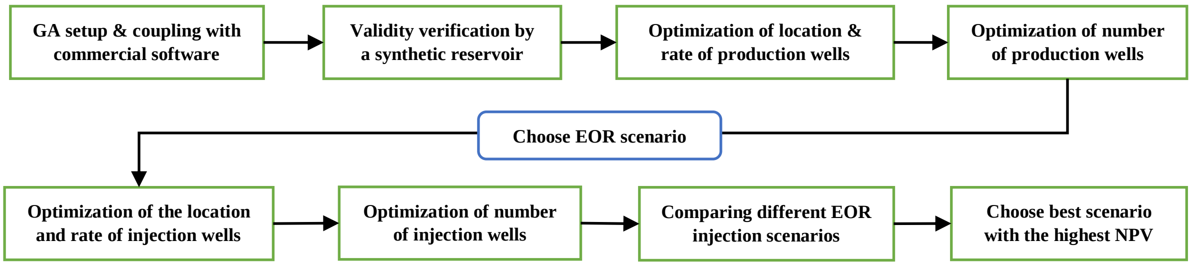

Figure 1

Flow chart of optimization process in the current work.

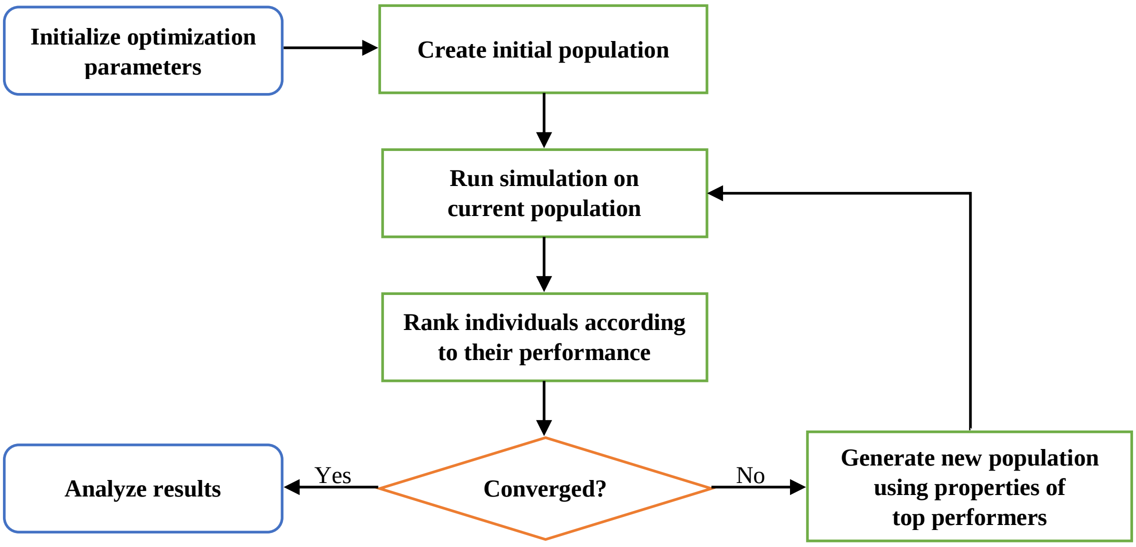

Figure 2

Flow chart of GA optimization procedure (Bukhamsin et al., 2010).

The basic theoretical background information on optimization using GA is presented in the following sections.

2.1. Optimization

Optimization is the process of adjusting the inputs of a device, a mathematical equation, or an experimental process with the aim of finding the maximum or minimum value in the output or solution. Due to the presence of many different variables, the lack of analytical solutions in most cases, and the nonlinearity of the reservoir development, the applications of gradient-based methods are limited; therefore, the use of random search tools seems necessary in problems with this level of complexity. GA is one of the most common algorithms which lies in this category. Another advantage of this method is that it can easily be combined with other algorithms and can also be used in parallel making up hybrid genetic algorithms.

The most important and basic type of genetic algorithms is the binary GA, in which the variables are coded in a binary form. In this algorithm, each variable is known as a chromosome, and a set of variables constitutes the initial population. In other words, chromosomes are made up of a string of zeros and ones (corresponding to the coordinates of each cell), and then they are randomly chosen and put together in different rows which constitute the population matrix. Thereupon, the objective function is calculated for each member, and a level of fitness is attributed to the selected chromosomes. In the next step, natural selection—for the survival of a population's individuals to form the next generation—occurs among those who have the minimum cost, whereas the rest of the chromosomes will be excluded from the population.

2.2. Crossover

In this step, two chromosomes which have a parent role and are selected based on their probability proportional to their relative fitness in the previous generation, are broken from some point (crossover point) and exchanged so that two new chromosomes (offsprings) could be produced as illustrated in Figure 3.

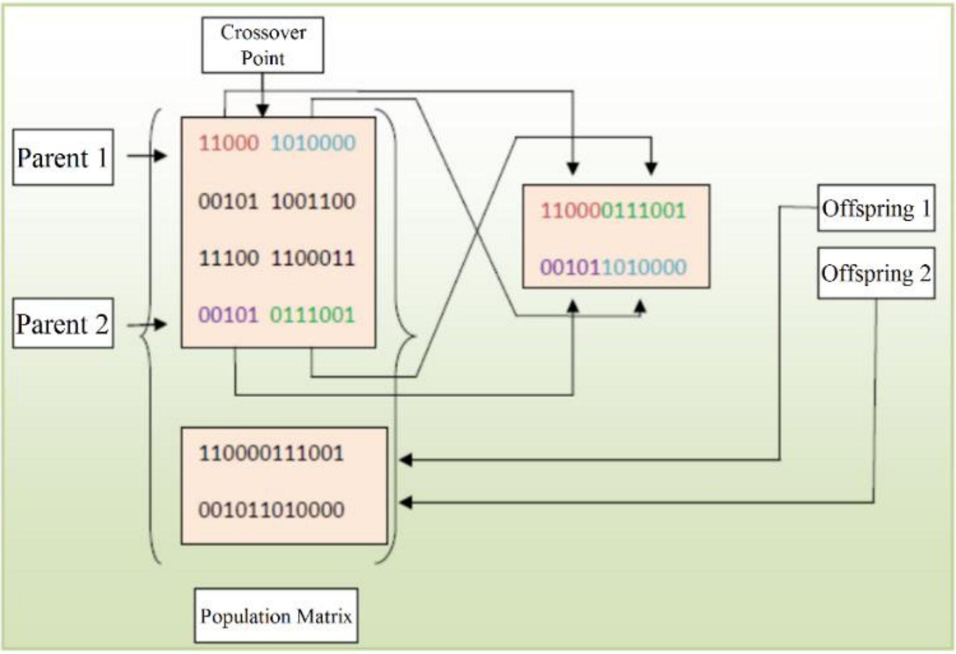

Figure 3

Combination/crossover process.

2.3. Mutation

Subsequent to the crossover, mutation occurs. Mutation is another way by which GA evaluates the cost function. To account for genetic diversity, single point mutation switches a random digit from 0 to 1 or vice versa, thereby forming the new chromosomes of the next generation and causing radical changes in the population. The mutation process is illustrated in Figure 4.

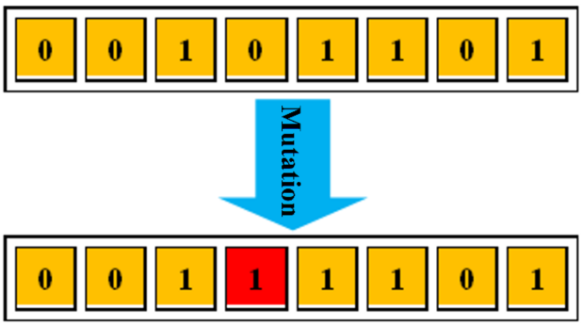

Figure 4

Mutation process.

After the population is completely constructed, the cost function associated with the offspring is calculated. The results of this stage are used as the initial population in the next step. This whole process would be repeated until the final stage is reached, that is, one of the termination conditions for the GA is established.

2.4. Termination conditions for GA

There are different approaches to finishing an optimization algorithm. The following methods can be the suitable options for such conditions:

- Reaching a certain number of generations;
- Completely using the allocated budget (computation time/money);
- Finding an individual (child solution) which meets the minimum criteria;
- Obtaining the maximum degree of fitness for the children, or when no other, better results can be achieved.

In the following sections, the application of GA in the current work is investigated, and the conditions, variables, constraints, and objective function used for the reservoir under study are provided. Furthermore, the validity of the code is verified using a synthetic reservoir.

2.5. Optimization variables

The selected optimization variables, while not depending on each other, must be in a very strong correlation with the objective function. Moreover, their count must also be low since the lower the number of the variables of a problem is, the lower its complexity is. The parameters optimized in this study are the number of wells, well coordination/location, the flow rate (production/injection) of each well, injection fluid, and the suitable EOR scenario to be used for ultimate recovery maximization. However, optimization with GA is performed on three basic variables. The first two independent variables are the number of reservoir grids in the *i* and *j* directions. Since all the wells drilled in the field development phase are vertical and completed in all layers, grids in the *k* direction were not considered. The third variable is the production/injection rate of the wells. As for the rest of the parameters (optimal number of wells, injection fluid, and EOR scenario), the optimum state is found by changing the variables one by one, repeating the optimization process, and comparing the different conditions to find the situation which yields the highest NPV.

2.6. Establishing the initial population

In order to increase the convergence speed of the program in reaching the optimum solution, a series of restrictions were defined for the genetic algorithm and the commercial simulator as follows:

a. Constraints applied to GA

- $1 < X <$ The number of grids in *i* direction;
- $1 < Y <$ The number of grids in *j* direction;
- $1 < n <$ The number of layers;
- Production and injection wells should not both be placed in the same grid;
- No similar chromosomes should be produced within a population:
- Since the calculation of the objective function is time consuming, the chromosomes of the previous population should not be entered into the objective function.

b. Constraints applied to the commercial simulator

- Maximum oil production rate is 10 Mbbl/day;
- Maximum water injection rate is 12 Mbbl/day;
- Maximum gas injection rate equals 40 MMscf/day;
- Maximum GOR allowed for each well equals 10 Mscf/stb;
- Maximum WC allowed for each well is 0.3 before water injection and 0.8 after water injection;
- Minimum production rate from each well equals 500 bbl/day.

2.7. Definition of the objective function

In the optimal development of oil fields, parameters such as cumulative oil production or NPV are usually regarded as the objective function. In certain cases, however, other functions may also be taken into account. For instance, the objective function could be defined as the minimum water-cut, the minimum produced gas, the minimum amount of injected water and gas, etc.

The objective function assigns a quantitative measure to a set of specific values for the variables (chromosomes). By incorporating the objective function, the optimization algorithm leads to improving the variables in order to achieve the optimal value for the objective function. The objective used in this work was considered to be the project net profit defined as: *Net profit = Total revenue – Total expenses*.

The earnings in this study are comprised of proceeds from sales of oil, gas, and condensates (if available). Moreover, the expenses include drilling costs, water and gas injection costs, repair and maintenance, and costs associated with the water disposal of the product. The economic model used in this work is based on the work of Yeten (2003), in which NPV is calculated according to a constant annual effective discount as given below:

$$NPV = \left[\sum_{n=1}^{Y} \sum_{p=l,g,w} \frac{1}{(1+i)^n} . Q_p^n . C_p\right] - C_d - C_{op} \tag{1}$$

$$C_d = \sum_{n=1}^{well\ count} C_{CAPEX} + L_{tot,n} C_{drill} \tag{2}$$

where, i stands for annual percentage rate (inflation rate), and Y is the total number of discount years. Q_p^n represents the rate of the production or injection of phase *p* (oil, gas, or water) in year *n*, and C_p is the revenue/cost per barrel of cubic feet of phase *p* (oil, water, or gas); C_d, C_{op}, and C_{CAPEX} stand for the total cost of drilling, operating costs, and capital expenditures of the well (tax expenses) respectively. $L_{tot,n}$ and C_{drill} also represent the total drilling length of the *n*th well and price per each foot of drilling respectively.

It should be noted that the coefficient of C_p is the interest rate (positive value) when the production phase is oil or gas, and it is the price index (negative value) either when the production phase is water or when gas or water are being injected. To calculate the exact value of the abovementioned objective function, one should predict the inflation rate in the following years, which is very difficult and needs to be managed by an economist. Therefore, the incomes and expenses were calculated based on year 2012, and an average of 10% was chosen for the inflation rate. The costs and incomes involved are presented in Table 1. In each simulation run, C_d is calculated according to the depth of each well and the given values of C_{drill} and C_{CAPEX} (Equation (2)). NPV is then calculated using Equation (1) by regarding the injection rates given as the inputs, the production rates obtained from the simulation outputs, C_p of each flowing phase, total simulation time (Y), inflation rate (i), C_{op}, and calculated C_d.

2.8. Validity verification of the optimization program

For any program which optimizes a specific process, one must ensure the validity of the optimization procedure; this rule stands true for GA as well. To validate the program and to ensure that the algorithm converges to the optimum answer, a simple homogeneous and isotropic reservoir was assumed. Table 2 lists the properties of this reservoir. It is intended that eight production wells and one injection well are drilled in this hypothetical reservoir, so the maximum net profit is obtained. It is known that for a homogeneous and isotropic reservoir, the situation where the injection well is at the center and the production wells are around the reservoir yields the optimum solution. To confirm the validity of the optimization program, the locations of the production wells were kept fixed in grids (1,1), (21,1), (1,21), (21,21), (11,21), (21,11), (11,1), and (1,11), but the location of the injection wells was regarded as the variable. This arrangement is illustrated in Figure 5.

Table 1

Economic parameters used for NPV calculations; the values are based on the economic conditions of year 2012 and experience in the field under study.

Economic parameter	Value
Revenue from oil sales ($C_{p=o}$)	\$50/bbl
Revenue from gas sales ($C_{p=g}$)	\$1/Mscf
Cost of water production ($C_{p=w}$)	\$10/bbl
Cost of water Injection ($C_{p=w_{inj}}$)	\$5/bbl
Cost of gas injection ($C_{p=g_{inj}}$)	\$1/Mscf
Cost of well drilling (C_{drill})	\$200/ft
Operating costs for each well (C_{op})	\$100/day
Inflation rate (i)	10%
Taxes (C_{CAPEX})	\$0/well

GA was used to find the optimal location of the injection well. Each individual of the population consisted of two variables *x* and *y*, where 1<*x* and *y*<21. After running the simulation for all the chromosomes, the net profit associated with the corresponding chromosomes was calculated. The program was implemented and was successful in determining the best location of the injection well (grid (11,11)). It can be seen in Figure 6 that GA attains the answer after 15 generations; thus, the ability of the algorithm to find the optimal solution is approved.

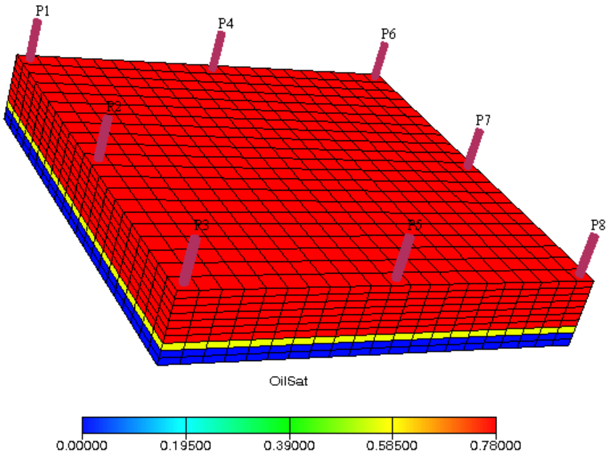

Figure 5

Locations of the production wells in the hypothetical model.

Table 2

Properties of the hypothetical reservoir.

Property	Value
Number of grids in *x* direction	21
Number of grids in *y* direction	21
Number of grids in *z* direction	10
Grid length in *x* direction	200 ft
Grid length in *y* direction	200 ft
Grid length in *z* direction	70 ft
Depth of the top layer of the reservoir	6000 ft
Porosity	0.25
Permeability	50 mD
Rock compressibility	0.00004 psi^{-1}
Oil density	45 $lb./ft^3$
Water density	63 $lb./ft^3$
Well diameter	0.5 ft
Active phases	Oil and water

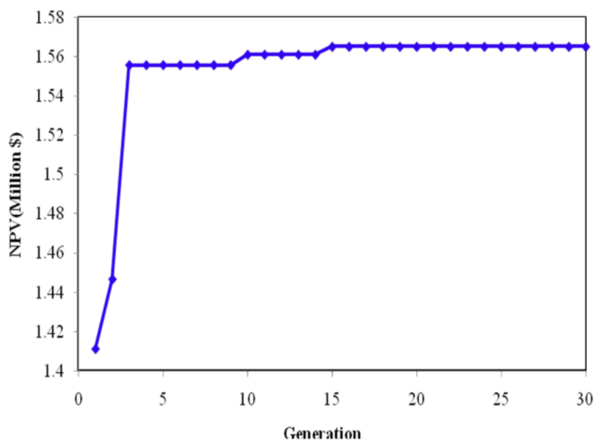

Figure 6

Maximum net profit gained in the hypothetical model.

3. Results and discussion

The reservoir model used in this study is a portion of one of the Iran southwest oil reservoirs. The reservoir is initially at 5620 psi and is located at the average depth of 11000 ft. Its dimension in *x*, *y*, and *z* directions is 16000, 16600, and 900 feet respectively with a pore volume of 10.5×10^9 cubic feet. The reservoir rock has connate water saturation of 35%, average porosity of 9%, and horizontal permeability of 15 mD. The reported density of the reservoir oil is also 31 °API. The characteristics of the reservoir are listed in Table 3.

Table 3

Characteristics of the real reservoir.

Property	Value
Initial reservoir pressure	5620 psi
Average depth of the top layer	11000 ft
Average horizontal permeability	15 mD
Average vertical permeability	5 mD
Average porosity	0.09
Pore volume	10.5×10^9 ft^3
Initial oil saturation	0.65
Total number of blocks	20×20×20
Number of active blocks	3868
Dimensions in *x*, *y*, and *z*	16000, 16600, and 900 ft
Average block size (*x*, *y*, and *z*)	800, 830, and 45 ft
Oil density	31 °API

Figure 7 depicts an overall schematic of the fluid distribution in the reservoir. It can be inferred from the fluid distribution that the reservoir has neither a significant gas cap nor an aquifer. Therefore, gas cap and water drive mechanisms are unlikely, and solution gas drive is probably the main mechanism of oil production. Consequently, after the natural production period ends and reservoir pressure drops below economic production threshold, the most proper and widely used scenarios for EOR is the injection of water, gas, or a combination of both (simultaneous water and gas injection). Hence, these scenarios are investigated and considered for the optimization study. To this end, the project is optimized in two parts.

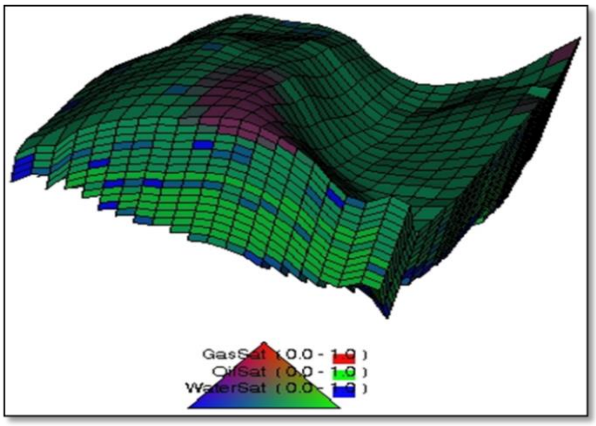

Figure 7

Fluid distribution in the real model.

3.1. Natural production

In this part, the optimization is carried out on the number, the location, and the production rate of wells, while no injection wells have yet been drilled. This scenario is maintained until the reservoir pressure reaches 70% of its initial value, which indicates an appropriate time for ending the reservoir natural production and employing primary and secondary EOR techniques according to previous full field studies. The optimized parameters in this scenario are as follows:

- Grid number of the well drilled in the *i* direction;
- Grid number of the well drilled in the *j* direction;
- Production rate from each well (Q_p).

This scenario was repeated for four, five, six, seven, and eight production wells, and the obtained results revealed that the highest net profit is gained in the case of six drilled wells (Figure 8). Table 4 lists the optimum rate and coordinates for each well.

Table 4

Optimized well locations and flow rates in the natural production mode.

Well ID	X	Y	Rate (bbl/day)
Production 1	4	4	3528
Production 2	13	4	4927
Production 3	16	4	7943
Production 4	7	13	3567
Production 5	11	17	7426
Production 6	16	17	5354

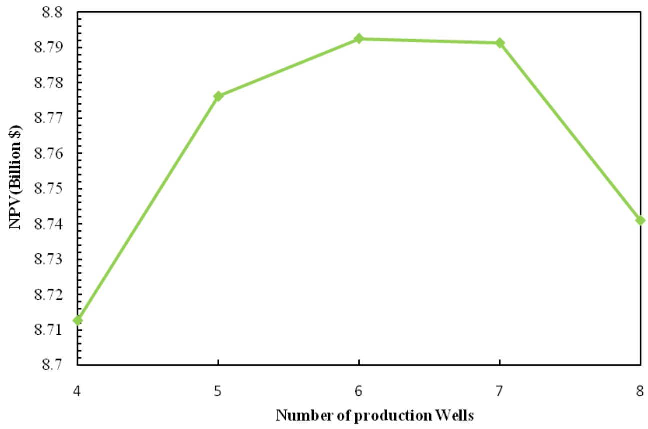

Figure 8

The comparison of NPV among different numbers of production wells.

3.2. Application of EOR methods

In the second part of the project, three different EOR scenarios are implemented with the aim of maximizing the ultimate recovery through drilling new injection wells. The number, the location, and the injection rate of the injection wells are to be optimized using GA, and the production rates of the existing wells are re-optimized.

a. First scenario: water injection

By injecting water, in addition to maintaining the reservoir pressure, the sweep efficiency is also improved. The optimization parameters in this scenario are the following:

- Grid number of the injection well to be drilled in the *i* direction;
- Grid number of the injection well to be drilled in the *j* direction;
- Rate of production wells (Q_p);
- Water rate in water injection wells (Q_{iw}).

This scenario was executed for up to four injection wells, and the results (see Figure 9) demonstrates that the maximum net profit is gained for the case of six production wells and three injection wells. Table 5 also tabulates the optimized characteristics of each well.

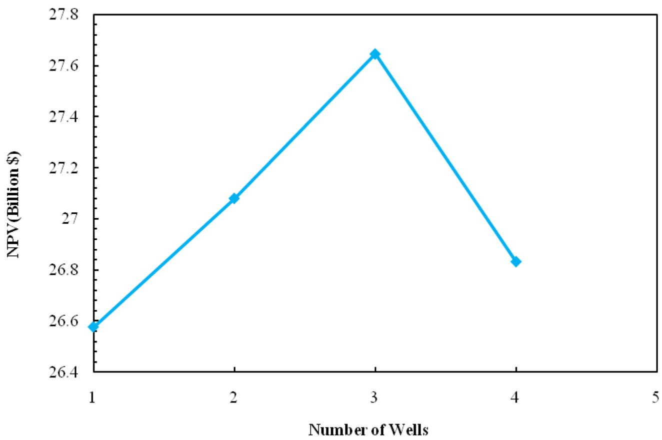

Figure 9

The comparison of NPV among different numbers of water injection wells.

Table 5

Optimized locations and flow rates of wells in the water injection scenario.

Well ID	X	Y	Production rate (bbl/day)	Injection rate (bbl/day)
Production 1	-	-	7498	-
Production 2	-	-	7763	-
Production 3	-	-	7607	-
Production 4	-	-	7424	-
Production 5	-	-	7507	-
Production 6	-	-	4911	-
Injection 1	3	10	-	9016
Injection 2	9	9	-	10748
Injection 3	17	14	-	7149

b. Second scenario: gas injection

This scenario implements gas injection to the reservoir, and the optimized parameters considered are as follows:

- Grid number of the injection well to be drilled in the *i* direction;
- Grid number of the injection well to be drilled in the *j* direction;
- Rate of production wells (Q_p);
- Gas rate in gas injection wells (Q_{ig});

Several optimization runs were performed for one, two, three, and four gas injection wells, and, as can be seen in **Figure 10**, a combination of six production wells and three injection wells leads to the highest net profit. The specifications of the well are summarized in Table 6.

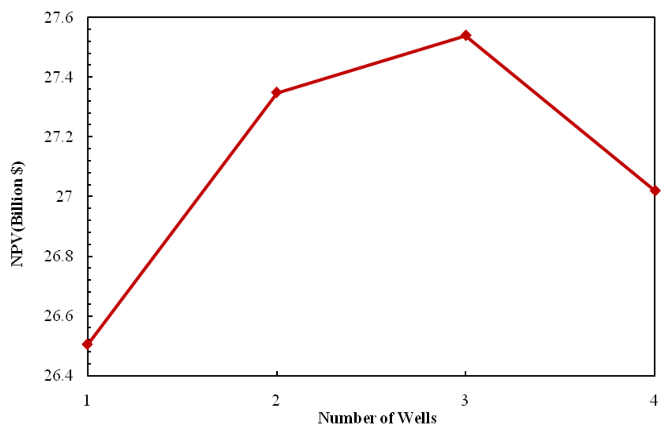

Figure 10

The comparison of NPV among different numbers of gas injection wells.

Table 6

Optimized locations and flow rates of wells in the gas injection scenario.

Well ID	X	Y	Production rate (bbl/day)	Injection rate (Mcf/day)
Production 1	-	-	7794	-
Production 2	-	-	7825	-
Production 3	-	-	7458	-
Production 4	-	-	7190	-
Production 5	-	-	7879	-
Production 6	-	-	4308	-
Injection 1	3	10	-	22930
Injection 2	11	14	-	28275
Injection 3	17	11	-	24700

c. Third scenario: simultaneous water and gas injection (SWAG)

In SWAG, water is injected from the upper reservoir blocks, and gas is injected from the lower blocks of an injection well. The optimized parameters of SWAG scenario include:

- Grid number of the injection well to be drilled in the *i* direction;
- Grid number of the injection well to be drilled in the *j* direction;
- Rate of production wells (Q_p);
- Water rate in water injection wells (Q_{iw});
- Gas rate in gas injection wells (Q_{ig});

SWAG was similarly performed for up to four injection wells, and the results obtained show that the highest net profit is gained for six production and three injection wells in the model (Figure 11). Table 7 also lists the optimum rates and coordinates of the wells in simultaneous water and gas injection scenario. Moreover, compared to the previous scenarios, the greatest net profit was gained in the case of SWAG. The comparison of NPV among various scenarios is demonstrated in Figure 12.

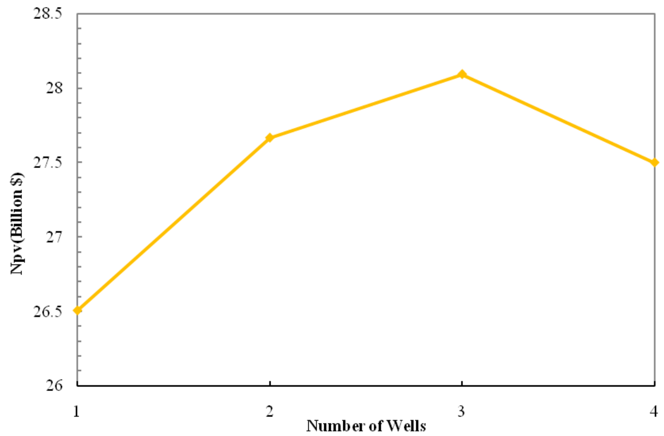

Figure 11

The comparison of NPV among different numbers of injection wells in SWAG.

Table 7

Optimized locations and flow rates of wells in the SWAG scenario.

Well ID	X	Y	Production rate (bbl/day)	Water injection rate (bbl/day)	Gas injection rate (Mcf/day)
Production 1	-	-	7559	-	-
Production 2	-	-	7623	-	-
Production 3	-	-	6822	-	-
Production 4	-	-	7017	-	-
Production 5	-	-	7648	-	-
Production 6	-	-	7748	-	-
Injection 1	4	16	-	5405	15644
Injection 2	10	13	-	5833	15708
Injection 3	15	12	-	8528	21481

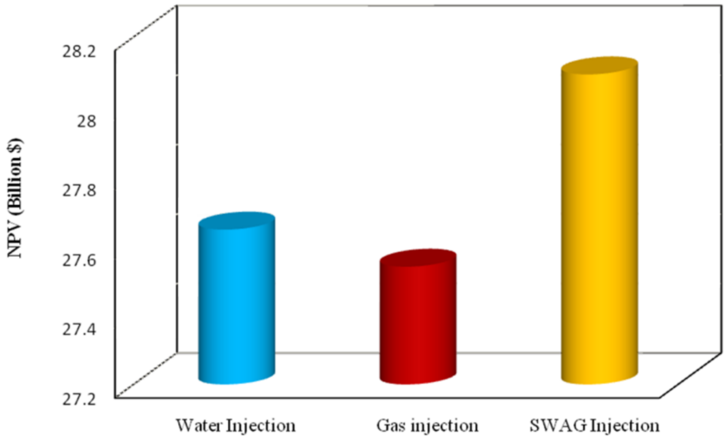

Figure 12

The comparison of project profitability (NPV) among various scenarios of water injection, gas injection, and SWAG by implementing six production wells and three injection wells.

4. Conclusions

One of the most important concerns about managing hydrocarbon reservoirs is the optimization of the location, the type, the number, and the rate of injection and production wells during EOR processes. In this study, after preparing the general framework of the optimization process by utilizing genetic algorithm and validating it using a synthetic reservoir model, a real reservoir was optimized. The location, the number, and the flow rate of the wells, including both production and injection wells, were optimized for a reservoir in the southwest of Iran. The results indicate that the maximum net profit is gained in case of six production well and three injection wells during a simultaneous water and gas injection scenario with an NPV equal to 28.1 billion dollars.

Moreover, genetic algorithm proved to be a useful tool for managing reservoir decision making and optimizing the location and flow rates of wells in order to achieve the maximum ultimate recovery and thus the highest economic profit. However, the current work has focused on optimizing the locations and flow rate of wells using GA, and other decision making variables, including horizontal/vertical wells, injection intervals, different EOR methods, and the optimum time of applying any scenario should be taken into account in future works.

Nomenclature

Abbreviations	
EOR	Enhanced oil recovery
GA	Genetic algorithm
GOR	Gas/oil ratio
HGA	Hybrid genetic algorithm
NPV	Net present value
SWAG	Simultaneous water and gas
WC	Water-cut
Symbols	
C_{CAPEX},	Capital expenditures of the well (tax expenses)
C_d,	Total cost of drilling of the well
C_{drill},	Price per each foot of drilling
C_{op},	Operating costs of the well
C_p,	Revenue/cost per barrel of cubic feet of phase p (oil, water, or gas)
i,	Annual percentage rate (inflation rate)
$L_{tot,n}$,	Total drilling length of the *n*th well
Q_p^n,	Rate of production or injection of phase *p* (oil, gas, or water) in year *n*
Y,	Total number of discount years
Units	
°API	American Petroleum Institute gravity
bbl.	Barrels
ft.	Feet
lb.	Pound mass
mD	Milli-Darcies
psi	Pound force per square inch
scf	Standard cubic feet
stb	Stock tank barrel

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