Economical Comparison of Surfactant and Water Flooding for Enhanced Oil Recovery

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Abstract: Although waterflooding is an effective process, surfactant flooding is used to recover oil from reservoirs by wettability alteration and interfacial tension reduction. Surfactants have been identified which can lower the IFT between oil and aqueous phase. The reduction of IFT leads to mobilization of the oil by buoyancy forces. In all the enhanced oil recovery processes, flow of displacing and displaced fluid in a petroleum reservoir is affected by the wettability of the reservoir rock.

Economical effectiveness is a main challenge in feasibility of any EOR method. In this study, we investigate the economical efficiency of both surfactant and water flooding by algorithm genetic optimization. One of the important optimization variables is well placement. Determining of the location of new wells is a complicated problem which depends on reservoir and fluid properties. Various methods have been suggested for this problem. Among these, direct optimization, although accurate, is impossible due to the number of simulation required.

Optimal placement of up to three surfactant injection wells was studied at two fields. One of the Iranian conventional field and a hypothetic fractured field. Injection rate and injection time was also optimized. The net present value of the surfactant and water flooding projects was used as the objective function. Profits and costs during the time period of the project were taken into consideration.

From the optimization results it will be shown that for the conventional reservoirs, the best wells should be located at the middle of the reservoir and increasing the injection rate and injection time also will increase the net present value. For the fractured reservoirs, the best wells should be located at the side of the reservoir and increasing the injection rate and injection time also will increase the net present value.

Key words: Surfactant, Water Flooding, Algorithm Genetic, Enhanced Oil Recovery, Economical Efficiency, Well Placement

1 INTRODUCTION

ENHANCED Oil Recovery (EOR) is oil recovery by injecting materials that are not present in a petroleum reservoir.

One of the important methods in EOR is chemical flooding such as surfactant flooding. Injection of surfactant increases the oil recovery [4]. Chemical flooding in the petroleum industry has a larger scale of oil recovery efficiency than water flooding. On the other hand, it is far more technical, costly and risky.

The well location is one of the most important aspects in production definition. Reservoir performance is highly dependent on well locations [5]. The process of choosing the best location for wells is basically trial and error. It is a time-consuming and demands high computational efforts, since the productivity depends on many variable related to well characteristics, reservoir and fluid properties, which can only be understood through numerical simulation. The use of an optimization algorithm to find a good position for the wells can be very useful to the process but it can also lead to an exhaustive search, demanding a great number of simulations to test many possibilities, most of the them disposable [6].

Numerical models are detailed and powerful predictive tools in reservoir management. While not perfect they are often the best representation of the subsurface. Optimization method run these numerical models perhaps thousands of times reaching for the most profitable solution to reservoir management questions. Because of the computational time involved optimization methodologies are not used as much as they could be. Various researchers have explored speeding up optimization by either using a speedier evaluation of the objective function or improving the efficiency of the optimization search itself.

The optimization algorithm used in this work is the genetic algorithm. The main characteristic of GA is the ability to work in a solution space with non-smooth and non-linear topology where the traditional methods generally fail. A reservoir simulator has been used in the present study. Genetic algorithm depends on the principle of artificial intelligence similar to Darwin's theory of natural selection. The genetic algorithm is coupled with the simulator in order to re-evaluate the optimized wells at each iteration.

2 BACKGROUND

Optimum reservoir management is an important theme in petroleum industry. Most of the studies related to reservoir performance optimization focus the well placement.

Aanonsen et al [7] proposed a method to optimize well locations under geological uncertainties based on response surfaces and experimental design. Multiple regression and kriging were used to reduce the number of simulation runs. A methodology to optimize the number and location of producer well in new fields was developed by Pedroso and Schiozer [8]. It was applied in primary recovery stage developed with vertical

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wells. The work utilizes parallel computing with intention to accelerate the process. Mezzeomo and Schiozer [9] proposed an optimization procedure based on reservoir simulation that evaluates both individual and wells and field performance. The methodology helps managers to make decisions that lead to an adequate recovery for the reservoirs, maximizing profits and minimizing risks associated to the investments.

The process to choose the location and the number of wells is not a simple procedure because of number of variables involved. The well behavior depends on the reservoir properties and interaction with other wells and it can only be predicted through numerical simulation. Therefore, each combination of number and well position must be tested by engineers. Many studies propose the use of an optimization algorithm to reduce the engineer's effort. The genetic algorithm has been used world-wide for this purpose due to its ability to work in a solution space with non-smooth and non-linear topology, where the traditional methods generally fail. The GA is an optimization method based on natural evolution process. It operates by defining an initial population with N individuals. Each individual is evaluated according to the value of the fitness function. Three main types of rules are used to drive the process: selection (or reproduction), crossover and mutation. Selection consists of determining a set of elite individuals from the population, based on fitness to the objective function: individuals with best objective function are candidates for elite. Crossover is the operation that tries to retain good features from the previous generation. It enables the algorithm to extract the best genes from different individuals and recombine them into potentially superior children. Mutation is the operation responsible to add diversity in a new generation.

Bittencourt and Horne [10] developed a hybrid algorithm based on direct methods such as genetic algorithm, polytope search and tabu search to obtain the optimal solution for problems related to reservoir development. Simulator was used as a data generator for the evaluation of the objective function, which involved an analysis of cash flow. Guyaguler et al [11, 12] have also be used genetic algorithm to reduce computational burden in well placement optimization problem upon uncertainties. Application of genetic algorithm and simulated annealing are presented by yang et al [13] to optimize production-injection operation systems. Ozdogan et al [14] also applied hybrid genetic algorithm for optimization of well placement under time-dependent.

3 Results and Discussion

3.1 Simulation Study

The objective of this study is optimization of surfactant flooding at two reservoirs. The genetic algorithm is the selected optimization method for this study. We coupled reservoir simulation software with genetic algorithm for optimization. While the cost of the drilling is so high and drilling process is time-consuming, in this study, the strategy was to use the available wells without drilling any new well for injection to eliminate the cost of drilling new wells. Therefore, it was assumed that up to three production wells of each reservoir can be changed to injection wells. Therefore by an appropriate optimization process, we are able to choose the best wells that are candidates for the surfactant flooding and water flooding. Also the injection rate of wells and the injection time should be optimized in order to maximize the production income. The schematic of the conventional and fractured reservoir is presented in Fig. 1 and Fig. 2 respectively. As it can be seen in the figures, there are eight production wells at each of them. The Iranian conventional oil reservoir is located at ILAM formation. The name of the wells is based on the formation name. The fractured reservoir is a hypothetic one.

The parameters that are selected as optimization variables are given in table 1.

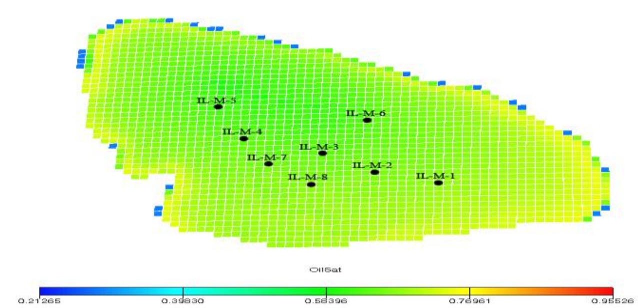


Fig. 1. The Schematic of the Conventional Oil Rreservoir

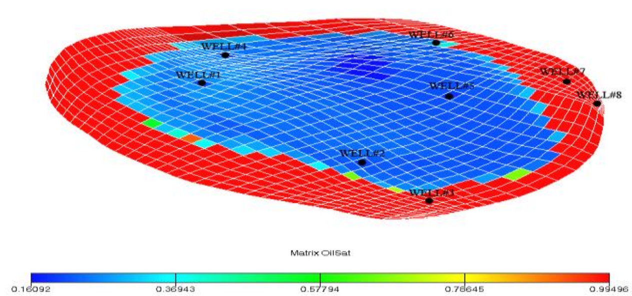


Fig. 2. The Schematic of the Fractured Oil Reservoir

Table 1
The Range and Number of Bits of Optimization Variables in Genetic Chromosome

Parameters	Ranges
Well Number	1-8
Injection Rate	100-400
Injection Time	1000-3000

3.2 The Fitness Function

In any optimization problem, there is an objective function which should be maximized or minimized. Genetic algorithm requires a fitness function (F(x)) to be defined and tries to Maximized this function. A fitness function is a particularly objective function that quantifies the optimality of a solution (chromosome) in a genetic algorithm so that the particular chromosome maybe ranked against all other chromosomes. The net present value is defined as the fitness function. The net present value is defined as the revenue from produced oil, after subtracting the cost of disposing produced water and the cost of injection water. During the optimization, objective function is defined as the Maximizing of Net Present Value.

Net cash flow (t) =Revenue (t) - Opex (t) (1)

Revenue (t) =Oil production (t) ×Oil price (t) (2)

OPEX(t)=Water production (t)×Water handling cost+Water injection (t)×WAter injection cost+ surfactant productionn(t)×surfactant handling cost (3)

CAPEX=Water injection installment cost+surfactant price (4)

NPV=Net cash flow-CAPEX (5)

For this study, NPV parameters were assigned as listed in table 2 [15].

TABLE 2
ECONOMIC PARAMETERS USED TO CALCULATE THE NPV

Economic Parameters	Value
Oil Price, $/bbl	126
Water Production Cost, $/bbl	32
Water Injection Cost, $/bbl	6
Surfactant Price, $/lb	1.5
Operating cost of Surfactant, $/bbl	0.25
Water Injection Installment Cost, $	10000000

3.3 Optimization results

In order to use genetic algorithm for optimization, setting up a number of parameters is required. The GA input parameters presented in table 3.

TABLE 3
GA INPUT PARAMETERS

Input Parameters	Value
Population Size per Generation	50
Maximum Number of Generations	100
Crossover Rate	0.8
Mutation Probability	0.1
Crossover Type	Single Point

The optimization of the six cases lasted approximately 1 day for each of them in a conventional PC to find the best values for surfactant flooding and water flooding process. The best values for conventional reservoir presented at Table 4 to Table 9. The NPV maximization versus generation plots is also shown at fig 3 to fig 5.

TABLE 4
OPTIMAL PARAMETERS FOR 1 INJECTION WELL FOR THE CONVENTIONAL RESERVOIR BY SURFACTANT FLOODING

Optimization Variable	Best Value
Well Number	2
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	1.7819×10^{10} $

TABLE 5
OPTIMAL PARAMETERS FOR 1 INJECTION WELL FOR THE CONVENTIONAL RESERVOIR BY WATER FLOODING

Optimization Variable	Best Value
Well Number	2
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	$1.7528 \times 10^{10}$$

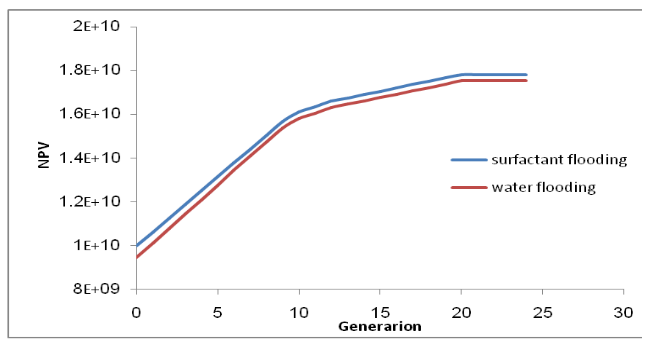


Fig. 3. The NPV vs. Generation Plot for 1 Injection Well for the Conventional Reservoir

TABLE 6
OPTIMAL PARAMETERS FOR 2 INJECTION WELLS FOR THE CONVENTIONAL RESERVOIR BY SURFACTANT FLOODING

Optimization Variable	Best Value
Well Number	2
Well Number	4
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	1.7221×10^{10} $

TABLE 7
OPTIMAL PARAMETERS FOR 2 INJECTION WELLS FOR THE CONVENTIONAL RESERVOIR BY WATER FLOODING

Optimization Variable	Best Value
Well Number	2
Well Number	4
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	1.6928×10^{10} $

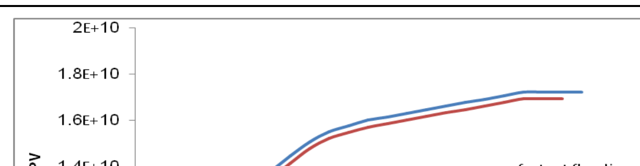


TABLE 8
OPTIMAL PARAMETERS FOR 3 INJECTION WELLS FOR THE CONVENTIONAL RESERVOIR BY SURFACTANT FLOODING

Optimization Variable	Best Value
Well Number	2
Well Number	3
Well Number	4
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	$1.6066 \times 10^{10}$$

TABLE 9
OPTIMAL PRAMETERS FOR 3 INJECTION WELLS FOR THE CONVENTIONAL RESERVOIR BY WATER FLOODING

Optimization Variable	Best Value
Well Number	2
Well Number	3
Well Number	4
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	$1.5792 \times 10^{10}$$

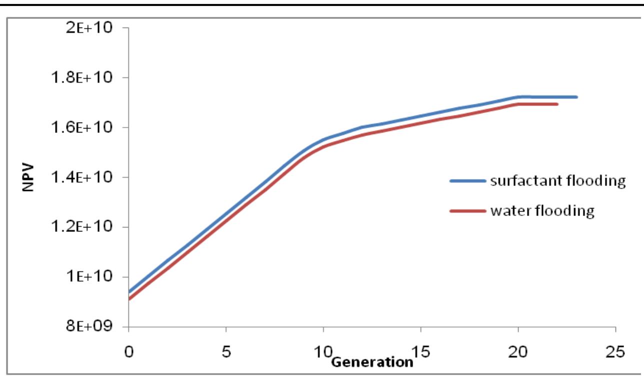


Fig. 5. The NPV vs. Generation Plot for 3 Injection Wells for the Conventional Reservoir

In each case, the total time of simulation is 10000 days and it can be seen that surfactant flooding is an efficient method respect to the water flooding for all cases. At all of the cases, by increasing the injection time and injection rate, the NPV increases. So we can say that the more injection time the more economic efficiency. One another point is that the best wells are the middle ones. By looking at the reservoir schematic, we will understand that the best candidate wells for surfactant injection and water flooding processes are the wells located at the middle of the reservoir since in this case we can recover more oil and most part of the reservoir is drained.
The best values for fractured reservoir obtained by optimization are presented in Table 10 to Table 15. The NPV versus generation plots of these cases are also shown in Fig 6 to Fig 8.

TABLE 10
OPTIMAL PARAMETERS FOR 1 INJECTION WELL FOR THE FRACTURED RESERVOIR BY SURFACTANT FLOODING

Optimization Variable	Best Value
Well Number	2
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	$1.3966 \times 10^{9}$$

TABLE 11
OPTIMAL PARAMETERS FOR 1 INJECTION WELL FOR THE FRACTURED RESERVOIR BY WATER FLOODING

Optimization Variable	Best Value
Well Number	2
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	$1.3928 \times 10^{9}$$

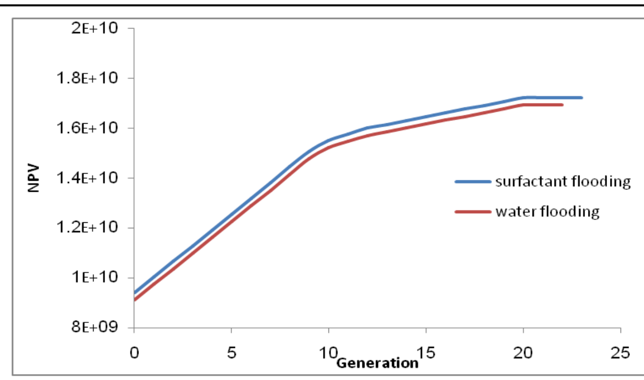


Fig. 6. The NPV vs. Generation Plot for 1 Injection Well for the Fractured Reservoir

TABLE12
OPTIMAL PARAMETERS FOR 2 INJECTION WELLS FOR THE FRACTURED RESERVOIR BY SURFACTANT FLOODING

Optimization Variable	Best Value
Well Number	1
Well Number	2
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	1.4617×10^9 \$

TABLE13
OPTIMAL PARAMETERS FOR 2 INJECTION WELLS FOR THE FRACTURED RESERVOIR BY WATER FLOODING

Optimization Variable	Best Value
Well Number	1
Well Number	2
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	1.4543×10^9 \$

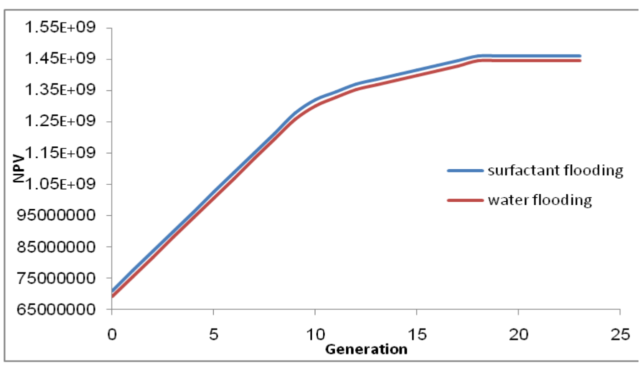


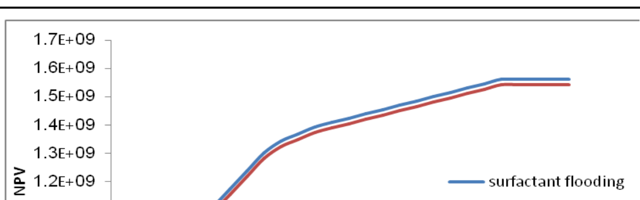
Fig. 7. The NPV vs. Generation Plot for 2 Injection Wells for the Fractured Reservoir

TABLE 14
OPTIMAL PARAMETERS FOR 3 INJECTION WELLS FOR THE FRACTURED RESERVOIR BY SURFACTANT FLOODING

Optimization variable	Best Value
Well number	1
Well number	2
Well number	4
Injection time	3000 day
Injection rate	400 bbl/day
Best NPV	1.5608×10^9\$

TABLE 15
OPTIMAL PARAMETERS FOR 3 INJECTION WELLS FOR THE FRACTURED RESERVOIR BY WATER FLOODING

Optimization Variable	Best Value
Well Number	1
Well Number	2
Well Number	4
Injection Time	3000 day
Injection Rate	400 bbl/day
Best NPV	1.5516×10^9\$



In each case, the total time of simulation is 10000 days and it can be seen that surfactant flooding is an efficient method respect to the water flooding for all cases. At all of the cases, by increasing the injection time and injection rate, the NPV increases. So we can say that the more injection time the more economic efficiency. In this case, the best candidate wells are located at the side of the Reservoir because when we choose the middle wells for injection, because of the fractures, the water cut increases and also the NPV decreases. So it can be concluded that for the surfactant flooding and water flooding projects, the location of injection wells are dependent to the reservoir characteristic and we should consider numerous variables.

5 CONCLUSIONS

- In this study, we knew that the surfactant flooding process is an efficient one and is dependent to numerous variables. The variables that are under our control are location of the injection wells, injection rate and injection time. Also it was shown that the surfactant flooding is dependent to the type of reservoir and reservoir characteristics.
- From the optimization results it can be concluded that for the conventional reservoirs, the best wells are located at the middle of the reservoir and increasing the injection rate and injection time also increase the net present value.
- For the fractured reservoirs, the best wells are located at the side of the reservoir and increasing the injection rate and injection time also increase the net present value.
- So before the chemical flooding like surfactant flooding, we must be familiar to type and characteristic of the reservoir.

REFERENCE

[1] Benyamin Yadali Jamaloei. R Kharrat: " Analysis of microscopic displacement Mechanisms of Dilute surfactant flooding in oil-wet and water-wet porous media", Transport porous media, 2008

[2] Baris Guyaguler: " Optimization of well placement in a Gulf of Mexico

Waterflooding Project'', SPE, Ronald N. Horne, SPE, (Stanford university) Leah Rogers, 2000

[3] Wathiq J. AL-Mudhafar .: '' Using optimization Techniques for determining optimal locationsof additional oil wells in south Rumaila oil field'', SPE, Iraqi south oil company; Mohammed S. AL-jawad, SPE, Baghdad university, 2010

[4] Zhangxin Chen. Yuanle Ma. Guo Chen.:'' A sequential numerical chemical compositional simulator'', Transport porous media, 2006

[5] O.Badru.:'' Well Placement Optimization in Field Development'', SPE, Stanford U. and C. S. Kabir, SPE, Chevron Texaco overseas petroleum

[6] Celio Maschio.:'' Production Strategy Optimization Using Genetic Algorithm and Quality Map'', SPE, Lincoln Nakajima, SPE, and Denis J. Schiozer, SPE, Unicamp, 2008

[7] Anonson, S.I., Eide, A. L., Holden, L.: ʻʻ optimization reservoir performance under with Application to well locationʼʼ, SPE 30710, SPE Annual Technical conference and Exhibition, Dallas, U.S.A., Oct, 22-25, 1995

[8] Pedroso Jr., C., Schiozer, D. J.: ʻʻ optimization location of well in fluid development using reservoir simulation and parallel computingʼʼ, Rio oil& Gas, Rio de Janeiro, Brazil, 2000

[9] Mezzomo, C.C., Schiozer, D.J.: ʻʻMethodology for water injection strategies planning optimization using reservoir simulationʼʼ, Paper 2002-121, 2002 Petroleum society's Canadian international Petroleum conference, Calgary, Alberta, Canada, Jun. 11-13, 2002

[10] Bittencourt, A.C., Horne, R.N.: ʻʻreservoir Development and design optimizationʼʼ, SPE 388895, SPE Annual Technical conference and Exhibition, San Antonia, TX, USA. Oct. 5-8, 1995

[11] Guyaguler, B., Horne, R.N.:ʻʻ uncertainty Assessment of well placement optimizationʼʼ, SPE 71625, SPE Annual Technical conference and Exhibition, New Orleans, Louisiana, USA. 30 Sep. to 3 Oct, 2001

[12] Guyaguler, B., et al: ʻʻ optimization of well placement in Gulf of Mexico waterflooding projectʼʼ, SPE 63221, SPE Annual Technical conference and Exhibition, Dallas, Texas, USA. Oct. 1-4, 2000.

[13] Yang, D, Zhang, Q. and Youngan GU, Y.ʼʼ Integrated optimization and control of the production- injection operation systems for Hydrocarbon reservoirsʼʼ, Journal of petroleum science and Engineering 37, 69-81, 2003.

[14] Ozdogan, U. and Horne, R. N. ʻʻ optimization of well placement under time-dependent uncertaintyʼʼ, SPE reservoirs Evaluation& Engineering, Vol. 9.N.2, April, 2006, PP. 135-145

[15] W. Wu, SPE, A. Vaskas, SPE, M. Delshad, G.A. Pope, SPE, and K. Sepehrnoori, SPE, The university of Texas, 1996.