Surfactant flooding is a technique used in enhanced oil recovery (EOR) to improve the efficiency of oil recovery from reservoirs.

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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. 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. 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 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 flooding projects was used as the objective function. Profits and costs during the time period of the project were taken into consideration.

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 [1]. 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. 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 [2].

Surfactant flooding process has to be optimized. 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 [3]. Various methods have been suggested for this problem. Among these, direct optimization, although accurate, is impossible due to the number of simulation required.

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 [4].

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.

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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 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 evaluate 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 been 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 uncertainty.

3. Surfactant-flooding

Surfactants are polar compounds, consisting of an Amphiphilic molecule with both hydrophilic and hydrophobic parts. The surfactants are classified as: anionic, cationic, Amphoteric and nonionic depending upon the nature of the charge present on hydrophilic group. The two basic features of the surfactants that make them unique for use in oil industry are their ability to lower oil-water interfacial tension and alter the reservoir wettability. Surfactant functions work by adding certain concentrations of surfactants to injection water to reduce the interfacial tension (IFT) between displacing and displaced phases [15]. In the process of surfactant flooding, the surfactant adsorbs onto the oil-water interface and surface of rock which may also make a wettability change of rock [16]. The experiment shows that the oil drops are becoming easier to deform when the water-oil interfacial tension reduces, so the resistance force lowers when the oil drops flow through the pore throat. With the decrease of IFT, the crude oil can disperse in the surfactant solution, meantime, the surface of oil drops are charged after adsorption, so the oil drops are not easy to stick onto the surface of rock particles.

The objective of this study is the simulation and optimization of surfactant flooding at two different reservoirs; conventional and fractured reservoirs. The schematic of the conventional and fractured reservoir is presented in Fig.1 and Fig.2 respectively.

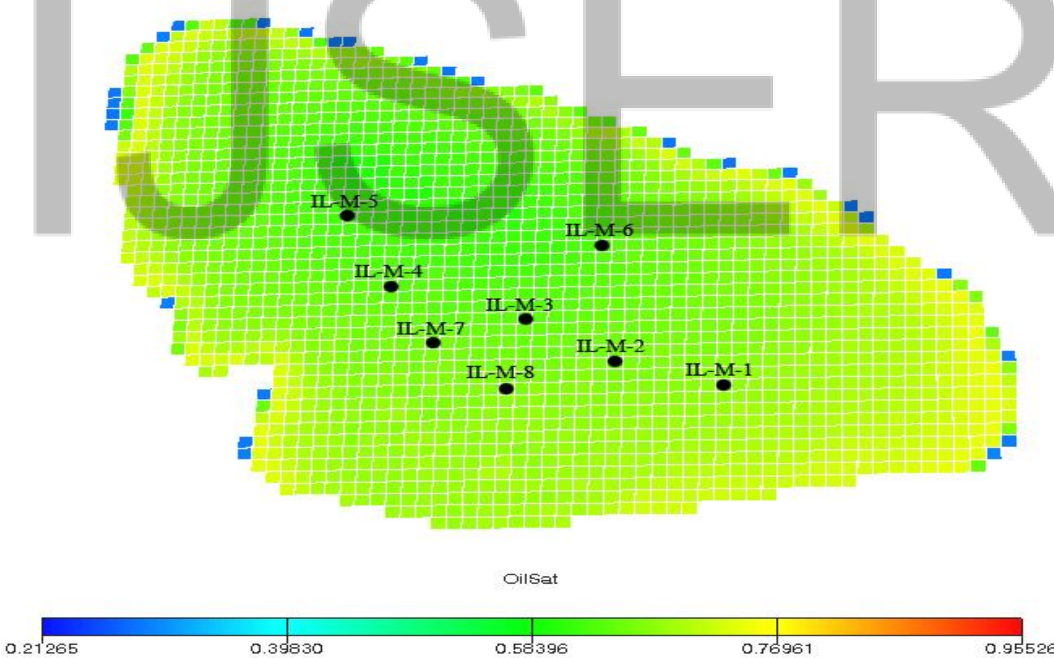


Fig.1 The schematic of the conventional oil reservoir

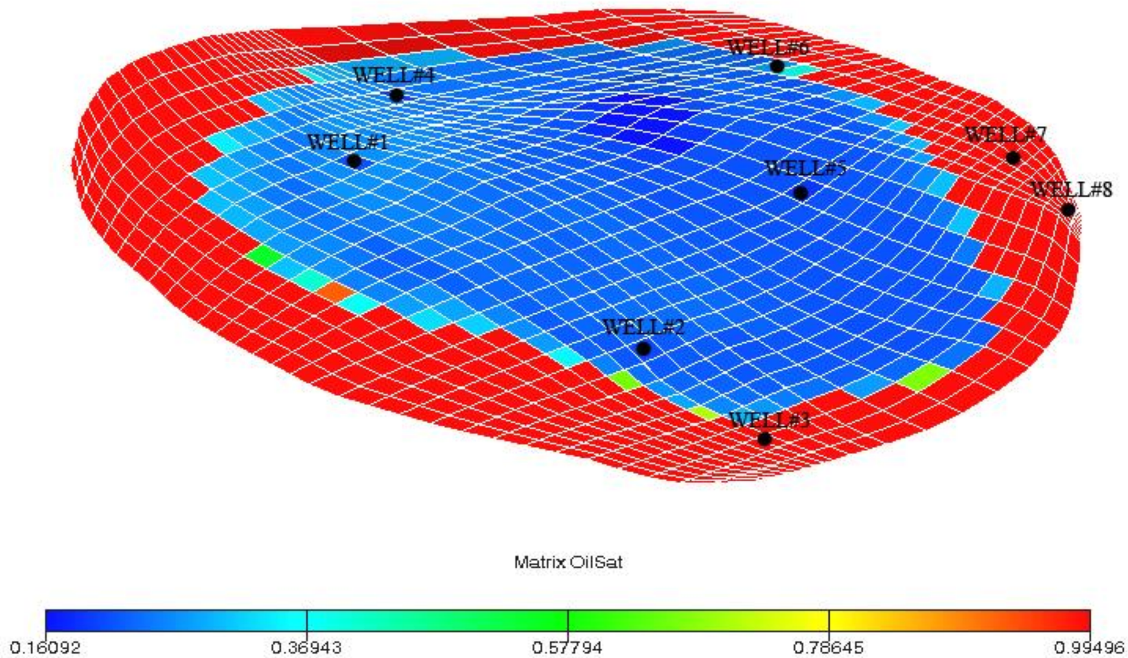


Fig.2 The schematic of the fractured oil reservoir

As shown in the figures 1&2, each reservoir consists of eight production wells. 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. In the first step, two new injection wells were located at each reservoir. The location of injection wells is shown at Fig. 3 and Fig. 4 respectively. The color bar shows the oil saturation at the reservoir.

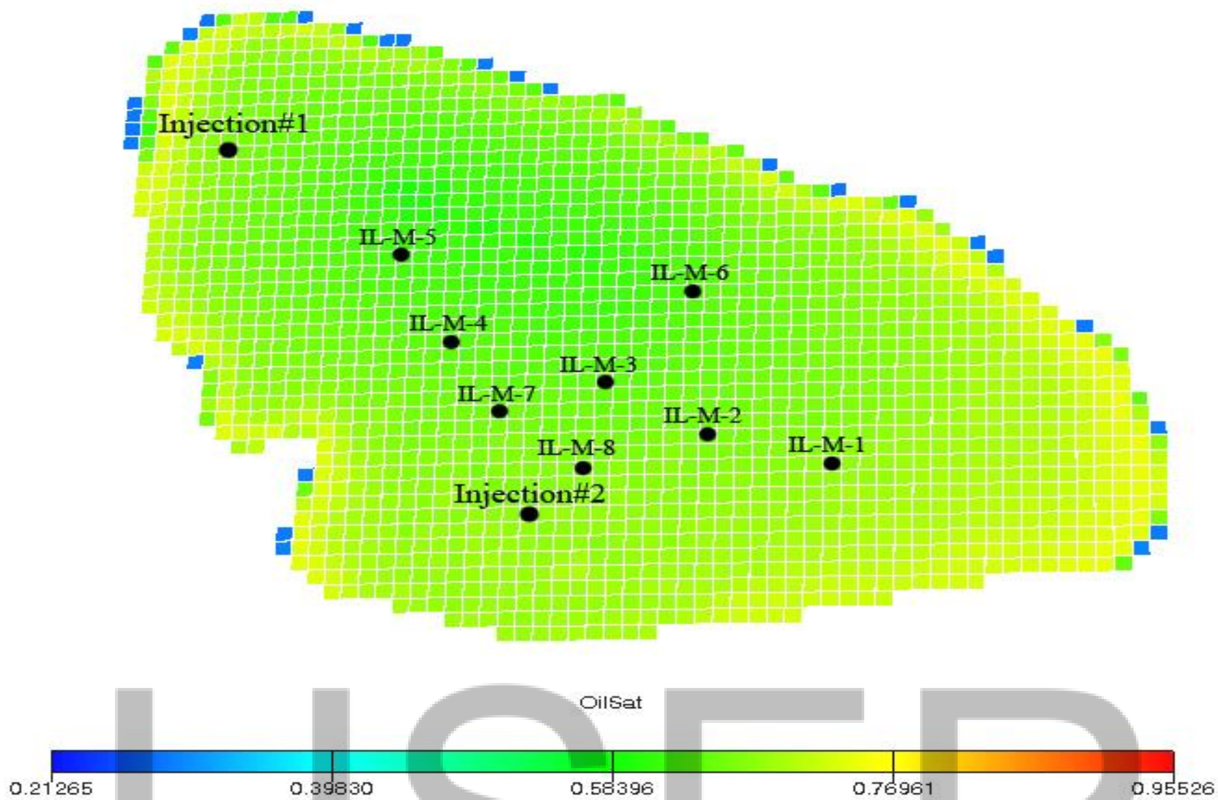
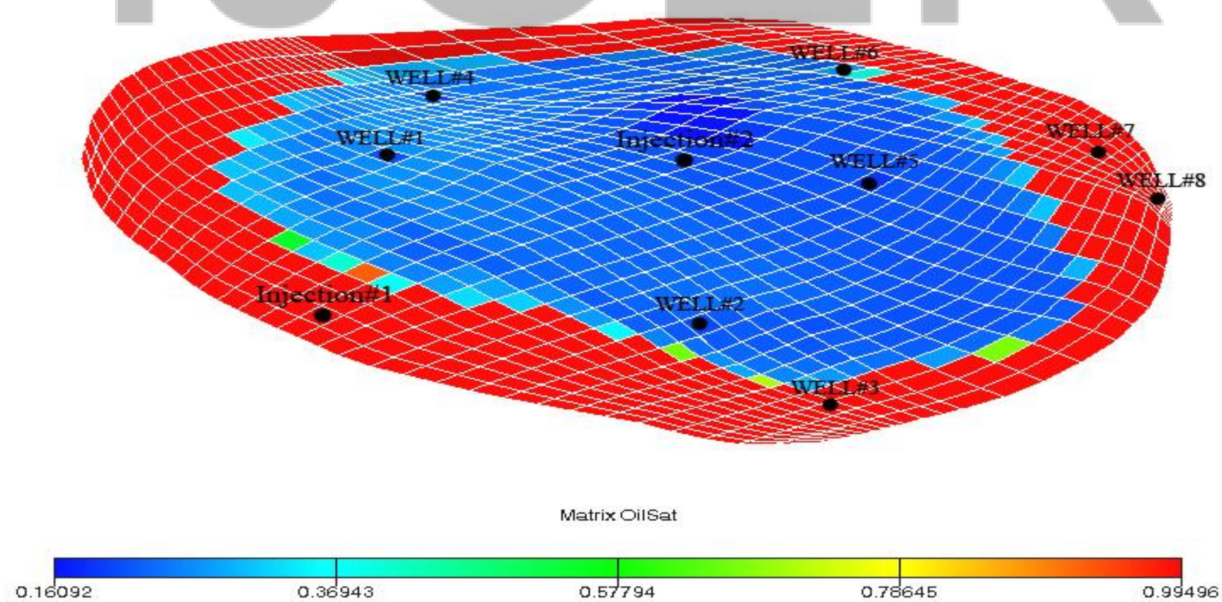


Fig. 3 the schematic of Iranian conventional oil reservoir



The fig. 4 the schematic of fractured oil reservoir

Then the surfactant flooding and waterflooding processes were simulated at both reservoirs at three injection rates. Finally the cumulative oil production respect to the natural production for both reservoirs was compared. The comparison between the plots of both reservoirs is shown at Fig. 5 to Fig. 19. The Oil recovery (%) for conventional reservoir and three injection rates and three cases (waterflooding and surfactant flooding and natural flooding) has shown at Table 1 and table 2.

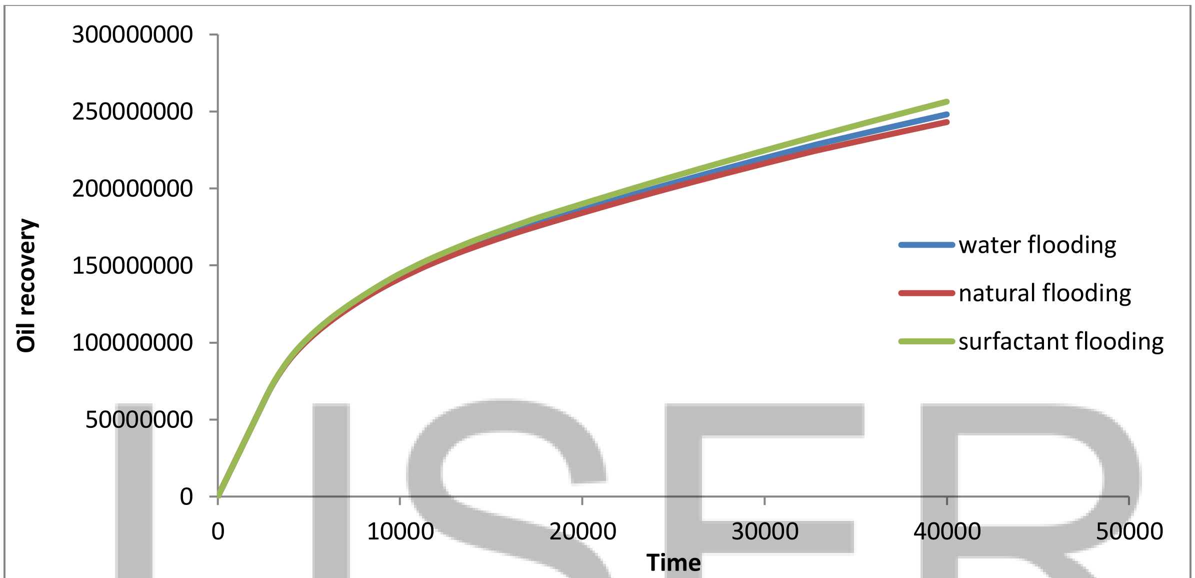


Fig 5 conventional reservoir at injection# 1 at 500 STB/day

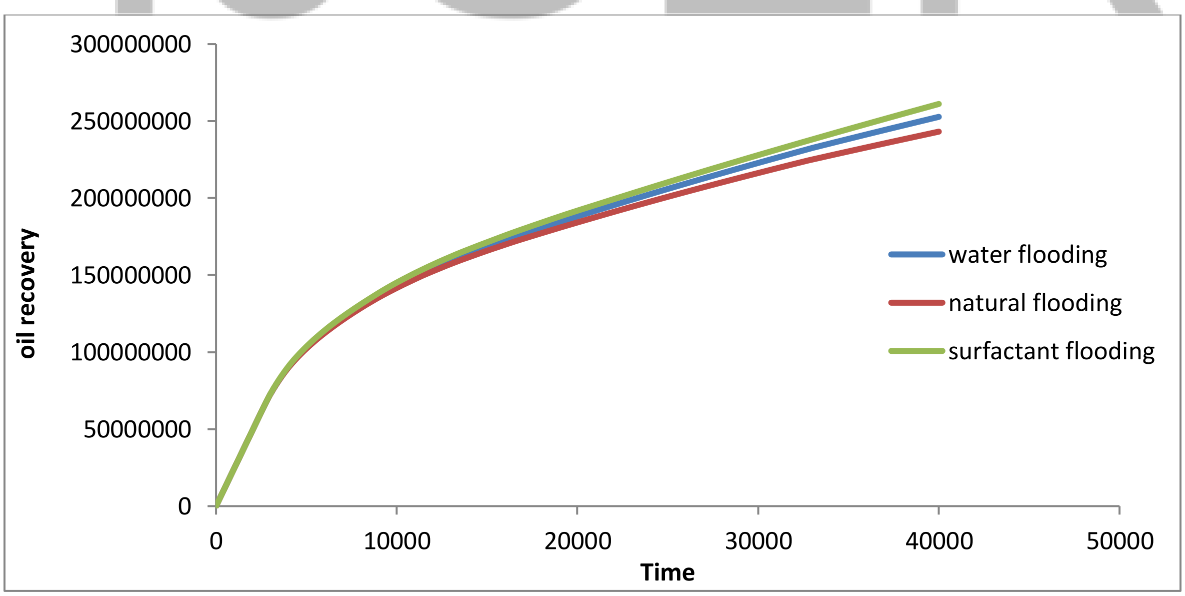


Fig 6 conventional reservoir at injection# 1 at 1000 STB/day

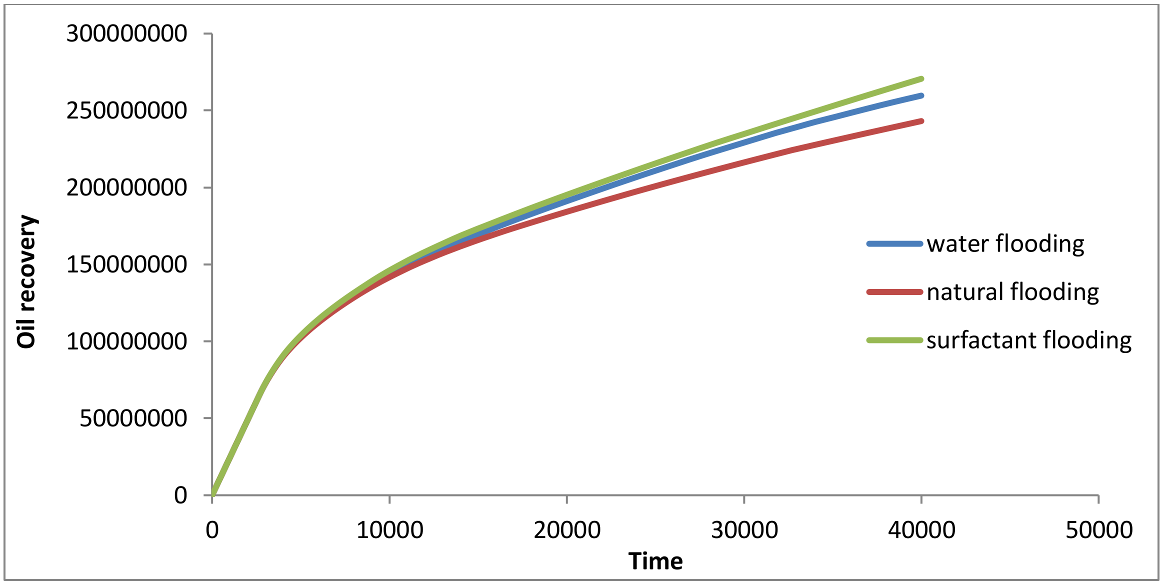


Fig 7 conventional reservoir at injection# 1 at 2000 STB/day

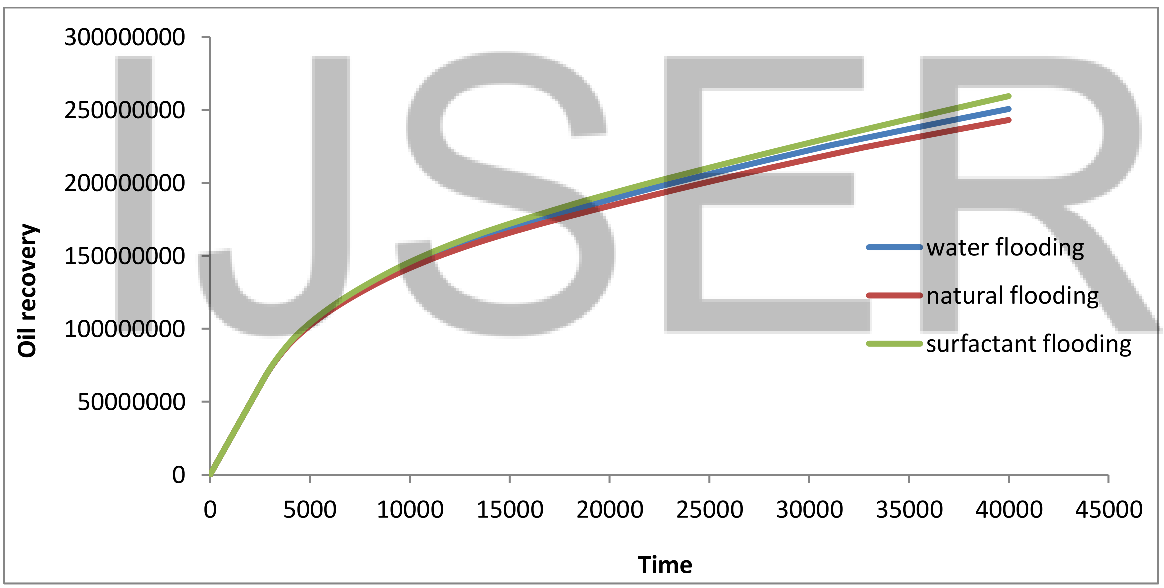


Fig 8 conventional reservoir at injection# 2 at 500 STB/day

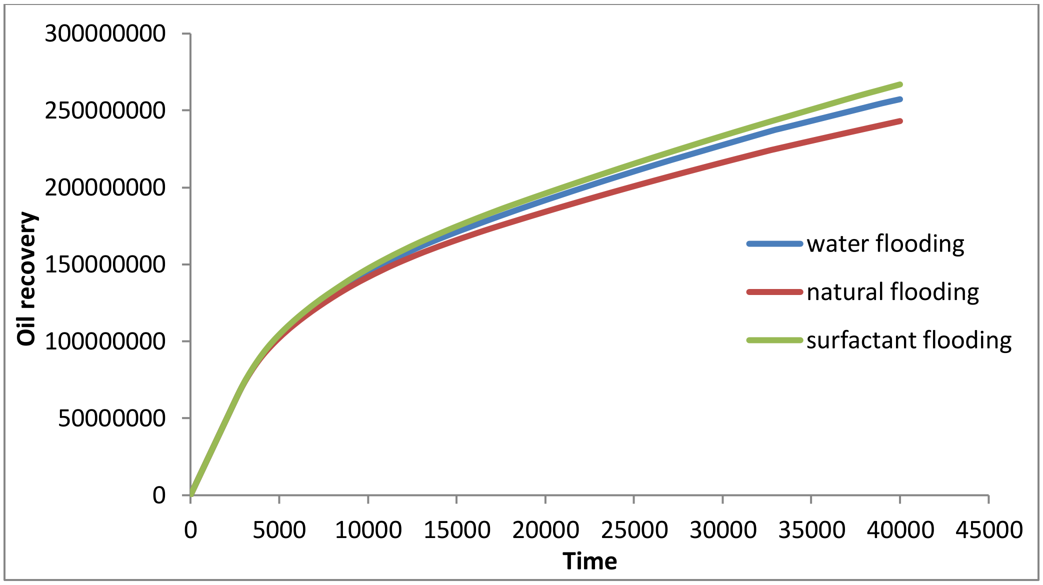


Fig 9 conventional reservoir at injection# 2 at 1000 STB/day

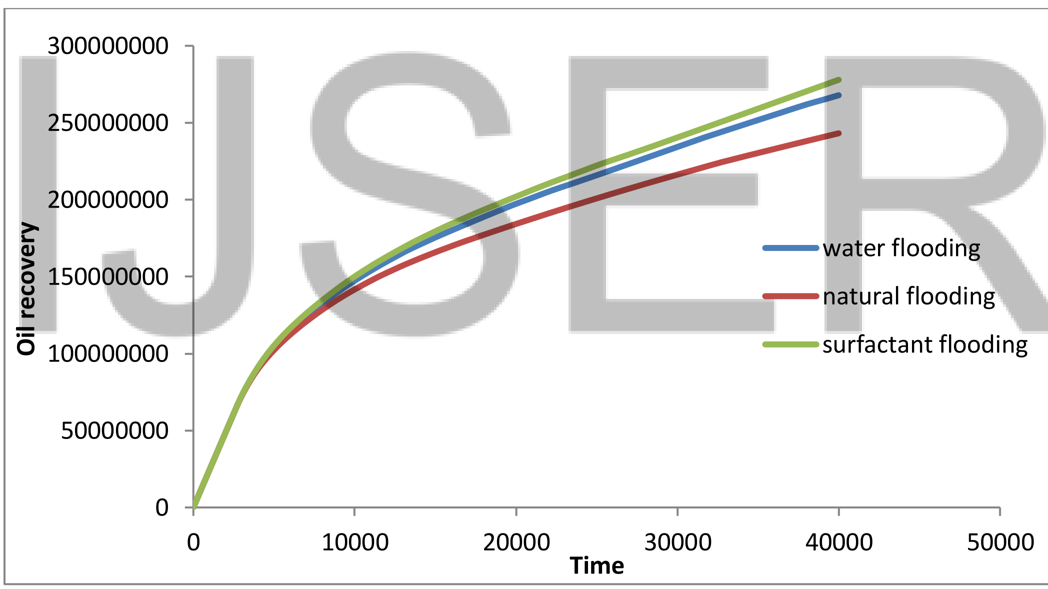


Fig 10 conventional reservoir at injection# 2 at 2000 STB/day

Table 1. Oil recovery at conventional reservoir at injection# 1

State	Oil Recovery (%)
Natural flooding	11.21
Waterflooding at 500 STB/day	11.251
Surfactant flooding at 500 STB/day	11.825
Waterflooding at 1000 STB/day	11.657
Surfactant flooding at 1000 STB/day	12.043
Waterflooding at 2000 STB/day	11.977
Surfactant flooding at 2000 STB/day	12.48

Table 2. Oil Recovery at conventional reservoir at injection# 2

State	Oil Recovery (%)
Natural flooding	11.21
Waterflooding at 500 STB/day	11.562
Surfactant flooding at 500 STB/day	11.969
Waterflooding at 1000 STB/day	11.869
Surfactant flooding at 1000 STB/day	12.313
Waterflooding at 2000 STB/day	12.354
Surfactant flooding at 2000 STB/day	12.817

First, we placed the injection# 1 well and did all simulations. As it can be seen, by increasing the injection rate, the waterflooding and surfactant flooding oil recoveries has increased respect to natural flooding state. Second, without presence of the injection# 1, we placed the injection# 2 well and repeated all steps. The results of this case are similar to the previous case. As it can be seen, the surfactant flooding oil recovery is greater than the waterflooding oil recovery with the same injection rate. The surfactant flooding oil recovery for injection# 2 is greater than the injection# 1 case. So we can conclude that the surfactant flooding is strongly dependent to the well location and injection rate. Another point is that these results are for a limited time of simulation. And ultimate oil recovery for waterflooding is about 30 to 40 % greater than the natural state and surfactant flooding ultimate recovery is approximately 10 to 15 % greater than waterflooding state. By doing this, we just wanted to show that surfactant flooding is an efficient method.

Both un-fractured and fractured formations will be addressed in this study. The driving force for displacement of oil in un-fractured systems is primitively the pressure gradient developed by displacing fluids from the injection well to the production well. This pressure gradient may be only a small contributor in fractured formations. In this case, spontaneous imbibition includes capillary pressure gradients and buoyancy, or gravity drainage. The contribution due to capillary pressure gradient may be diminished because of low interfacial tension.

In a fractured reservoir, fluids exist in two interconnected systems:

1- The rock matrix, which usually provides the bulk of the reservoir volume
2- The highly permeable rock fractures

Wettability and matrix block size are two major factors in fluid transfer between fracture and matrix. For an oil-wet fractured reservoir, containing only oil and water, water from an injection well or from an aquifer can flow in fractures easily and much faster than in the matrix. Gravity drainage can produce oil if the matrix block is thick enough to overcome the negative water-oil capillary pressure. This is true particularly for oil-wet fractured reservoirs [17].

If the matrix blocks are linked only through the fracture system, this conventionally could be regarded as a dual porosity single permeability, since fluid flow through the reservoir take place only in the fracture network with the matrix block acting as sources. If there is the possibility of flow directly between neighboring matrix blocks, there is conventionally considered to be a dual porosity dual permeability systems. So we did simulations for dual porosity and dual permeability cases. Results of dual permeability cases are shown at Fig 11 to Fig 16. The oil Recoveries (%) has shown at Table 3 and Table 4.

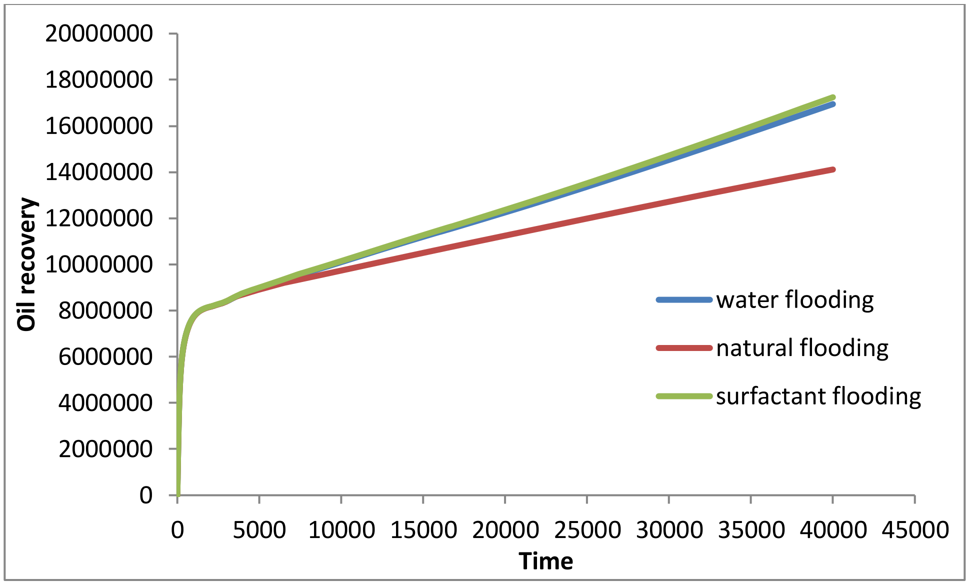


Fig 11 Dual Permeability reservoir at injection# 1 at 500 STB/day

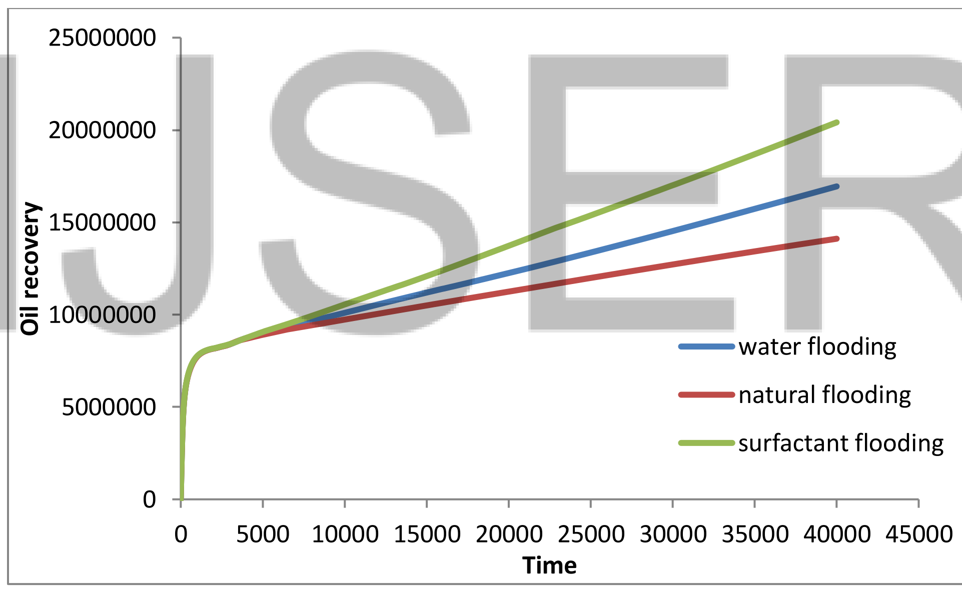


Fig 12 Dual permeability reservoir at injection# 1 at 1000 STB/day

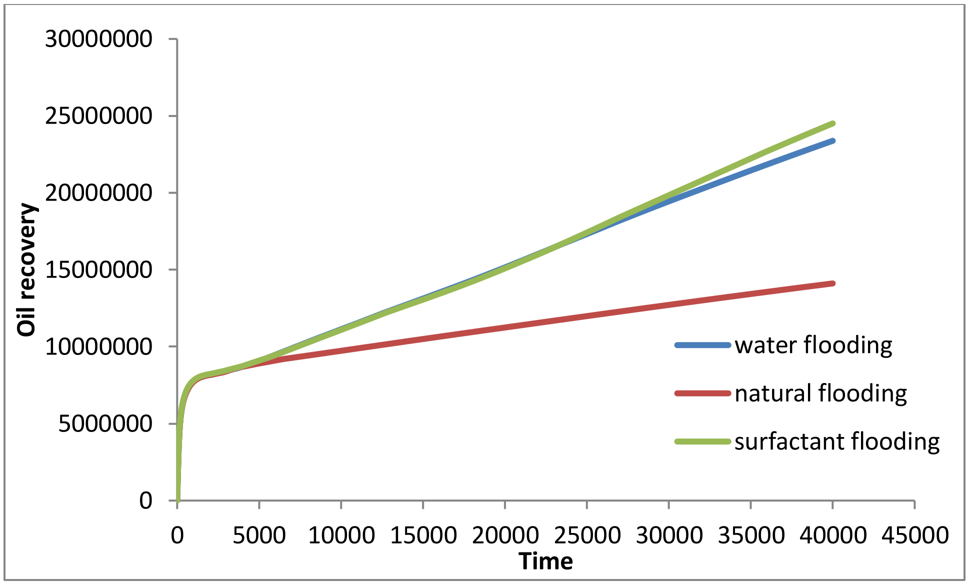


Fig 13 Dual permeability reservoir at injection# 1 at 2000 STB/day

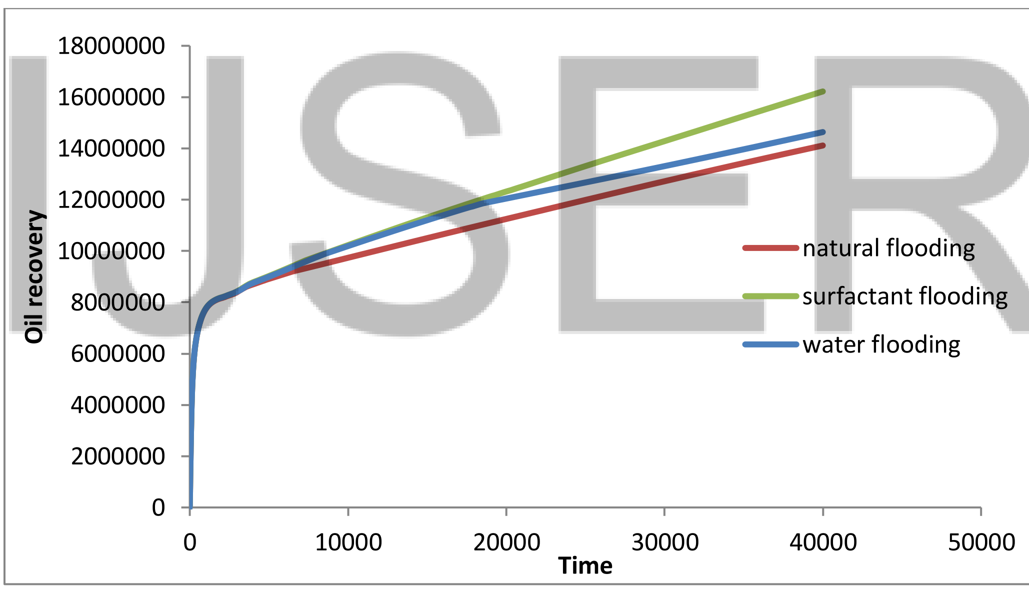


Fig 14 Dual permeability reservoir at injection# 2 at 500 STB/day

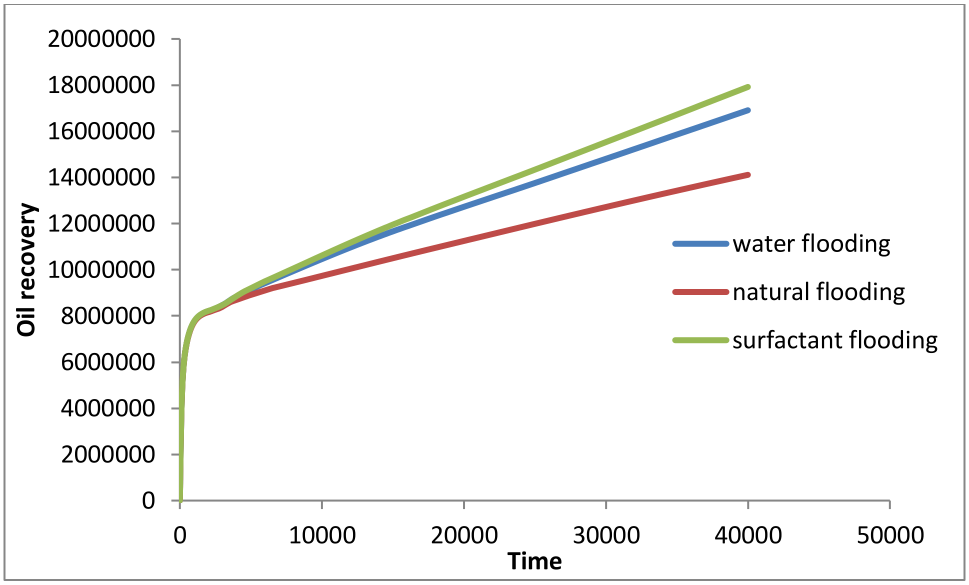


Fig 15 Dual permeability reservoir at injection# 2 at 1000 STB/day

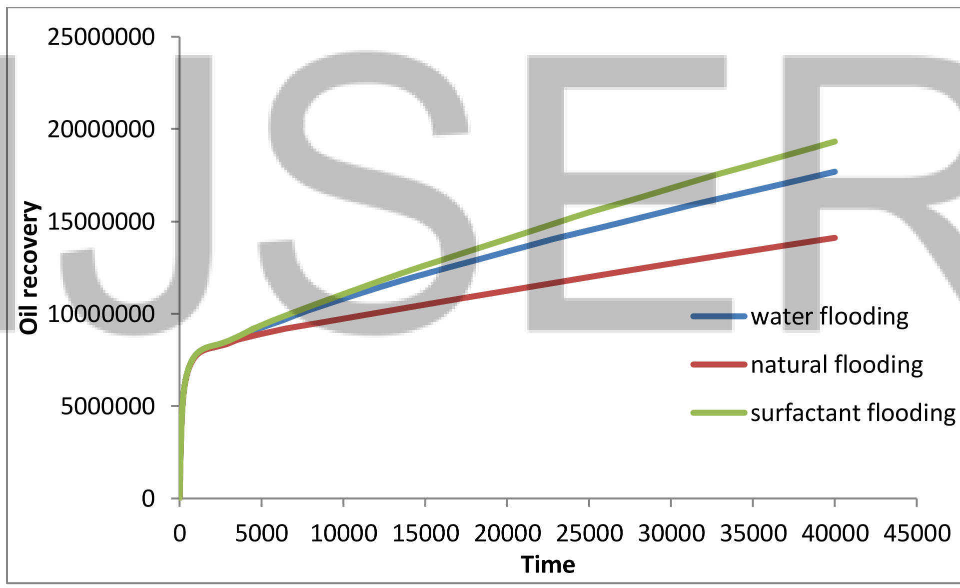


Fig 16 Dual permeability reservoir at injection# 2 at 2000 STB/day

Table 3. Oil recovery at Dual permeability reservoir at injection# 1

State	Oil Recovery (%)
Natural flooding	10.348
Waterflooding at 500 STB/day	12.246
Surfactant flooding at 500 STB/day	12.643
Waterflooding at 1000 STB/day	12.426
Surfactant flooding at 1000 STB/day	12.68
Waterflooding at 2000 STB/day	17.144
Surfactant flooding at 2000 STB/day	17.973

Table 4. Oil Recovery at Dual permeability reservoir at injection# 2

State	Oil Recovery (%)
Natural flooding	10.348
Waterflooding at 500 STB/day	10.732
Surfactant flooding at 500 STB/day	11.893
Waterflooding at 1000 STB/day	12.399
Surfactant flooding at 1000 STB/day	13.14
Waterflooding at 2000 STB/day	12.673
Surfactant flooding at 2000 STB/day	14.172

At First, we placed the injection# 1 well and did all simulations. As it can be seen, by increasing the injection rate, the waterflooding and surfactant flooding oil recoveries has increased respect to natural flooding state. Secondly, without presence the injection# 1, we placed the injection# 2 well and repeated all steps. The results of this case are similar to the previous case. As it can be seen, the surfactant flooding oil recovery is greater than the waterflooding oil recovery with the same injection rate. The surfactant flooding oil recovery for injection# 1 case is different from the recovery of injection# 2. So we can conclude that the surfactant flooding is strongly dependent to the well location and injection rate. Another point is that these results are for a limited time of simulation, so ultimate oil recovery for waterflooding and surfactant flooding are greater than such values. By doing this, we just wanted to show that surfactant flooding is an efficient method and dual-permeability reservoirs behave similar to conventional reservoirs. One reason is that in such reservoirs, fluid flow through the reservoir not only in the fracture network and there is the possibility of flow directly between neighboring matrix blocks.

Finally we did simulation for dual porosity reservoirs. Results of dual porosity case are shown in Fig. 17 to Fig. 19. The oil Recoveries (%) has shown at Table 5.

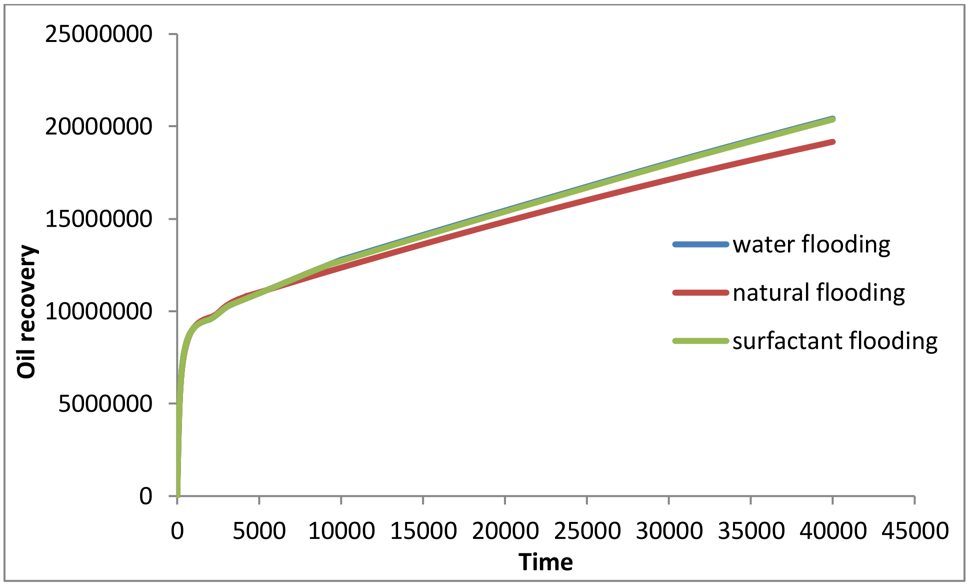


Fig 17 Dual porosity reservoir at injection# 1 at 500 STB/day

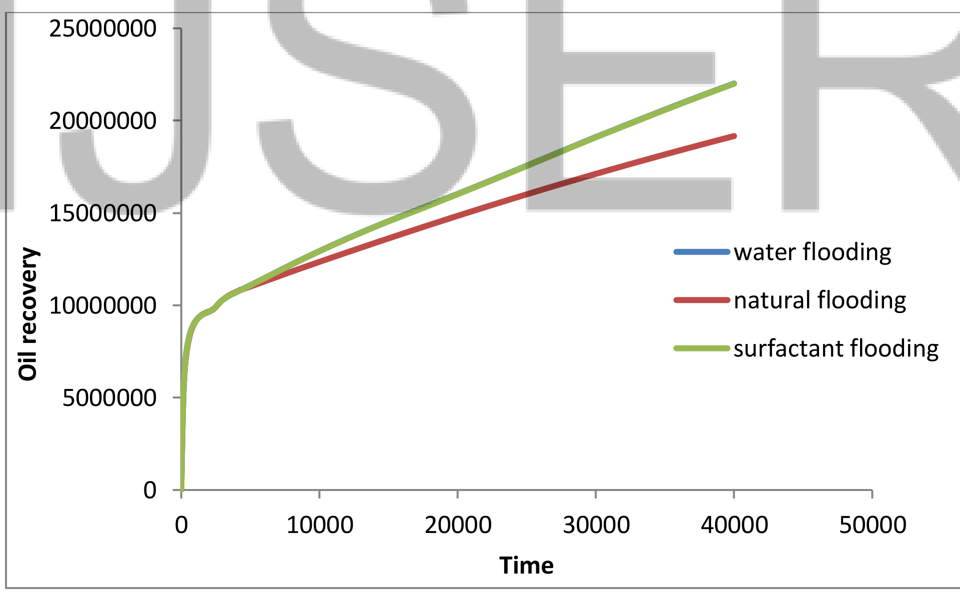


Fig 18 Dual porosity reservoir at injection# 1 at 1000 STB/day

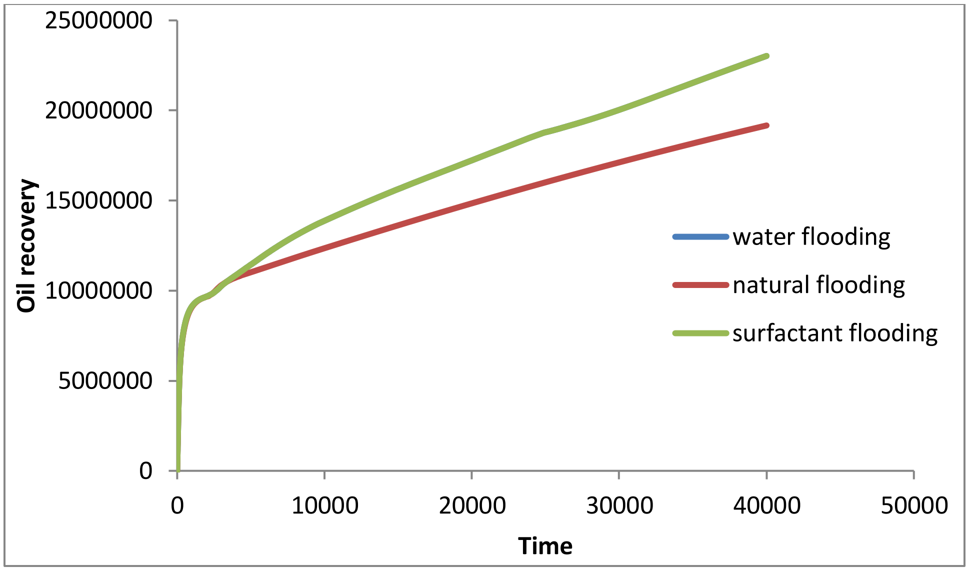


Fig 19 Dual porosity reservoir at injection# 1 at 2000 STB/day

Table 5. Oil recovery at Dual porosity reservoir at injection# 1

State	Oil Recovery (%)
Natural flooding	14.055
Waterflooding at 500 STB/day	14.93
Surfactant flooding at 500 STB/day	14.93
Waterflooding at 1000 STB/day	16.14
Surfactant flooding at 1000 STB/day	16.14
Waterflooding at 2000 STB/day	16.88
Surfactant flooding at 2000 STB/day	16.88

As it can be seen, the surfactant flooding process is not an efficient process respect to waterflooding process in dual-porosity reservoirs since the oil recovery of surfactant flooding is the same as the water flooding oil recovery. One reason is that the matrix blocks are linked only through the fracture system and fluid flow through the reservoir takes place only in the fracture network with the matrix block acting as sources and matrix networks are not interconnected and surfactant is not in direct contact to matrix network. In dual-porosity reservoirs, if we place an injection well near the production wells (like injection# 2), the water and surfactant flow through the fractures and early breakthrough occurs and water flooding and surfactant flooding recoveries maybe smaller than natural flooding. Surfactant has to be in direct contact to matrix to mobilize the oil by wettability alteration and IFT reduction mechanism. So we conclude that the surfactant flooding is inefficient process in dual porosity reservoirs and the behavior of these reservoirs is unlike to the dual permeability reservoirs.

Surfactant injection method in an oil-wet, dual-porosity model may not be effective because of the following reasons [17]:

1- Pressure gradient may be too small to displace oil from the matrix in fractured formations in contrast to the homogenous un-fractured reservoirs.
2- High permeable fractures could act like thief zones and bypass small fractures. In this case using mobility control agents like foam might be considered
3- Gravity difference between fracture and matrix could be ineffective to mobilize oil by chemical flooding depending on the matrix block height. The smaller block height, the less the effectiveness of gravity drainage.

4. Genetic algorithms

Genetic algorithms are search algorithms based on the mechanics of natural selection. They combine survival of fittest with a structured yet stochastic exchange of information of increase the efficiency of an otherwise purely random search. These methods were first used in the sixties by biologists to simulate evolution, based mainly on mutation patterns. The first attempt to use Genetic algorithms to optimize complex problems was in the seventies by john Holland in which the basic theory was formulated demonstrating the ability of bit chains to represent complex problems, and the capacity of simple transformation to improve those chains. In this work Holland [18], demonstrated that it was possible to find an optimal individual evaluating only a very small fraction of the population.

It is useful to comment on the main differences between genetic algorithms and traditional methods:

1. Direst manipulation of a coding
2. Search from a population and not from a point

3. Search via sampling, blind search
4. Search using stochastic operators

All these differences make genetic algorithm able to overcome many of the limitations of the traditional methods, especially the continuity and derivability of the objective function.

4.1. Genetic algorithms structure

In the following lines, the different processes that make up a genetic algorithm and their variations are analyzed in detail. The figure 7 shows a flowchart of the GA used in this work.

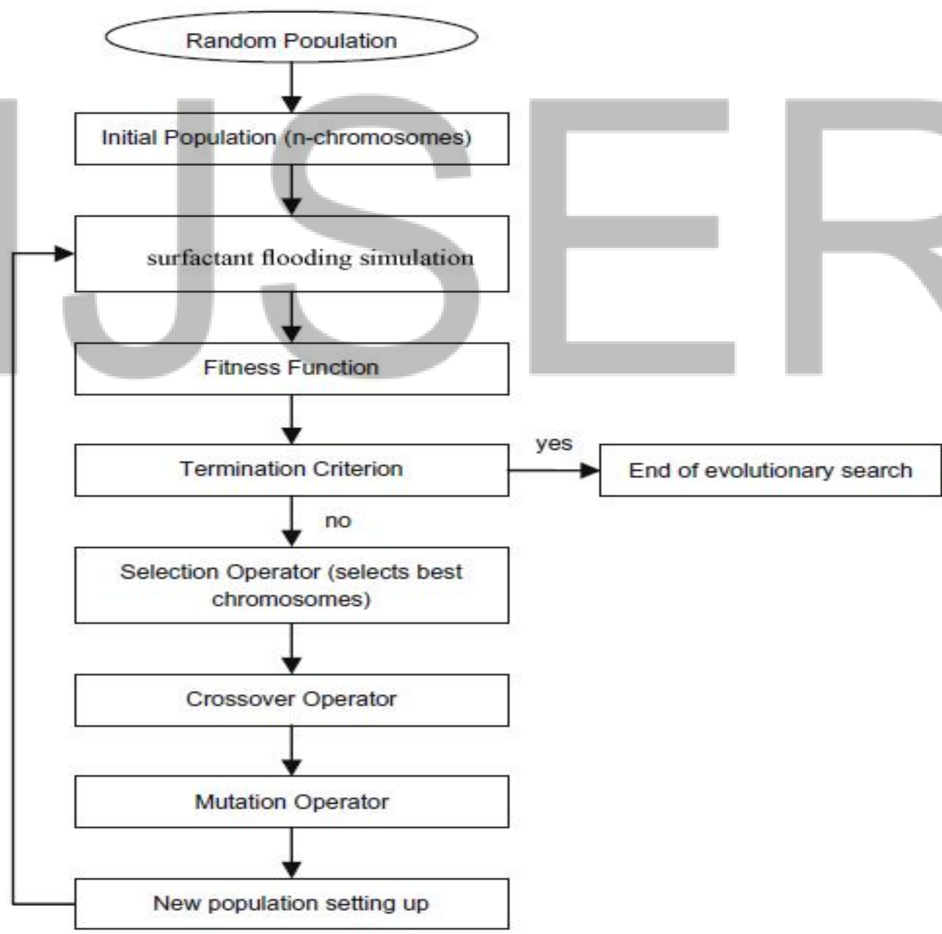


Fig 7. Flowchart of optimization with genetic algorithm

Population generation

This is the first step. Here the problem variables are codified to form a chromosome, and an initial population is generated, either randomly or using algorithms which assure an appropriate coverage of the population. Alternatively part of the initial population can be introduced manually if the programmer has an interpretation of where the optimum might be.

The chromosomes are made of bytes, each byte representing one of the codified problem variables. Each variable is codified usually in binary code, or grade, although in the program developed the codification has been decimal, to simplify the algorithm, although this has further implications which will be discussed later in detail.

4.2. Evaluation

In the evaluation step all the chromosomes are evaluated. This evaluation can be as complex as desired, and can incorporate technical and economical functions. This evaluation ranks all the chromosomes from the best to worst. In biological terms, this represent the fitness of every chromosome to survival and reproduction. When using complex evaluations with penalizing restrictions, it is important not to use very strong penalties as it can restrict the evolution of the population. A biological paradoxical analogue is illustrative, ’’ if it is impossible to fly with heavy loads, and in order develop wings the weight has to be increased, then no animal would ever fly’’.

4.3. Reproduction

This is probably the most complicated step, and the one with the highest number of variations. In this step the new generation of chromosomes is created from the parent chromosomes. The mating and survival of the chromosomes is based upon their evaluation. There are different methods to create new populations. Those in which the selection of the parents is merely deterministic (Ranking methods), being the chromosomes selected to mate based only on their merit. Those in which the selection is random (heuristic selection), so that the fittest chromosomes have the highest chance of being reproduced. Finally mixed techniques like tournament, are those where all the chromosomes are mated in pairs and only the ones with the highest merit survive.

Once the parent chromosomes have been chosen, a new generation has to be created from them. These processes are used: mating (crossover), mutation and elitism. In elitism a few of parent chromosomes are passed intact to the new generation. In mating, two chromosomes are crossed and the children chromosome is created by a combination of the parents code. The last method in mutation, in which a part of the parent code is randomly changed.

The mix of these three mechanisms is complex and various authors have studied their influence in obtaining the absolute maximum and the convergence speed, regarding the problem to be optimized (Udias [19], Bittencourt [20]). In the program developed for this dissertation the influence of these processes can be controlled and the effects of changing these parameters have been studied.

4.4. Elitism

Elitism is mainly used to make sure that the best chromosomes would survive to the next generation. In this way we will be assured that every new generation would be at least as good as the previous ones. However if a great part of the population is protected in this way, The creation of new chromosomes is slowed and thus, it can affect global convergence, if the chromosomes protected represent a local maximum.

4.5. Mating

Mating is the main mechanism by which new chromosomes are created and is highly advised that most of the chromosomes will be allowed to cross. In mating two parents chromosomes are selected, and a random point in their strings is selected. This point is used to break the parent chromosomes and their parts are mixed creating two new chromosomes.

4.6. Mutation

Mutation is basically a mechanism to assure that new genetic material is introduced. It is recommended that at least a small degree of mutation is allowed so that in case of stagnation (local maximum) the process can move to other maximums. The mutation process can move to other maximums. The mutation process can be applied either prior to mating or after mating. Another possibility is to mate only part of the population, and mutate the rest.

5. Results and discussion

5.1 Simulation study

The objective of this study is optimization of surfactant flooding at two different 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 parameters that are selected as optimization variables are given in table 1.

Table 1 The range and number of bits of optimization variables in genetic chromosome

Parameters	Number of bits	Ranges
Well number	3	1-8
Injection rate	2	100-400
Injection time	2	1000-3000

5.2 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.

$$Net\ cash\ flow(t) = Revenue\ (t) - \ Opex(t)$$

$$Revenue\ (t) = Oil\ production\ (t) \times Oil\ price\ (t)$$

$$\begin{aligned} OPEX(t) = {} & Water\ production\ (t) \times Water\ handling\ cost \\ & + Water\ injection\ (t) \times WAter\ injection\ cost \\ & + \ surfactant\ productionn(t) \times surfactant\ handling\ cost \end{aligned}$$

$$CAPEX = Water\ injection\ installment\ cost + surfactant\ price$$

$$NPV = Net\ cash\ flow - CAPEX$$

For this study, NPV parameters were assigned as listed in table 2 [21].

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

5.3 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 are also shown at fig 8 to fig 10.

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* □□□
Injection rate	*400* □□□/□□□
Best NPV	1.7528×10^{10}\$

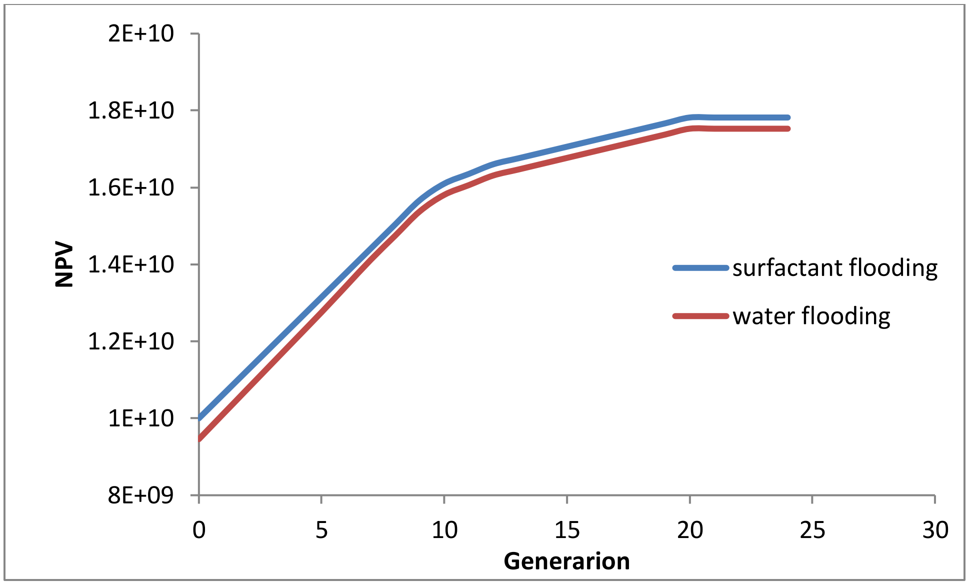


Fig 8. The NPV vs. generation plot for 1 injection well for the conventional reservoir

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* □□□
Injection rate	*400* □□□/□□□
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* □□□
Injection rate	*400* □□□/□□□
Best NPV	1.6928×10^{10} \$

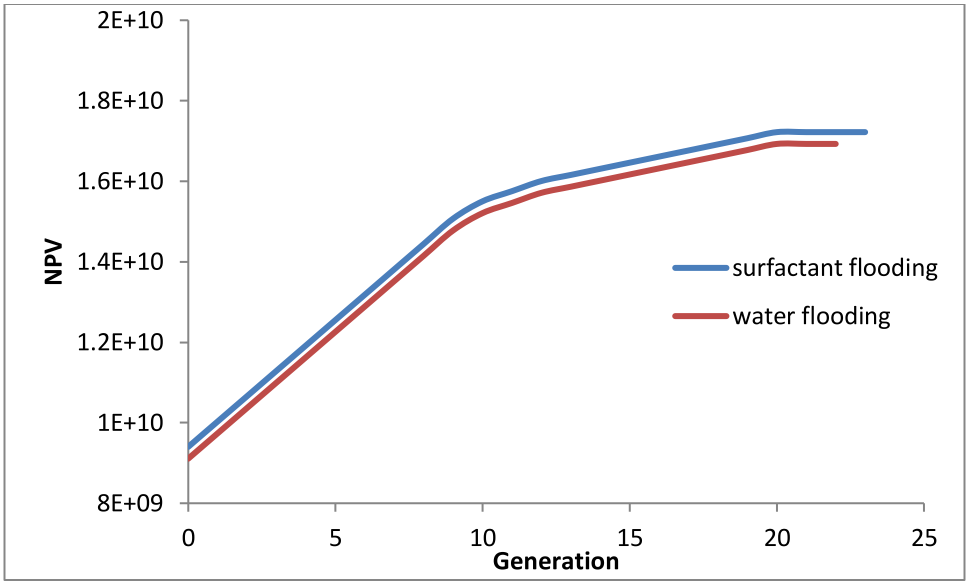


Fig 9. The NPV vs. generation plot for 2 injection wells for the conventional reservoir

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* □□□
Injection rate	*400* □□□/□□□
Best NPV	$1.6066 \times 10^{10}\$$

Table 9. Optimal parameters 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* □□□
Injection rate	*400* □□□/□□□
Best NPV	$1.5792 \times 10^{10}\$$

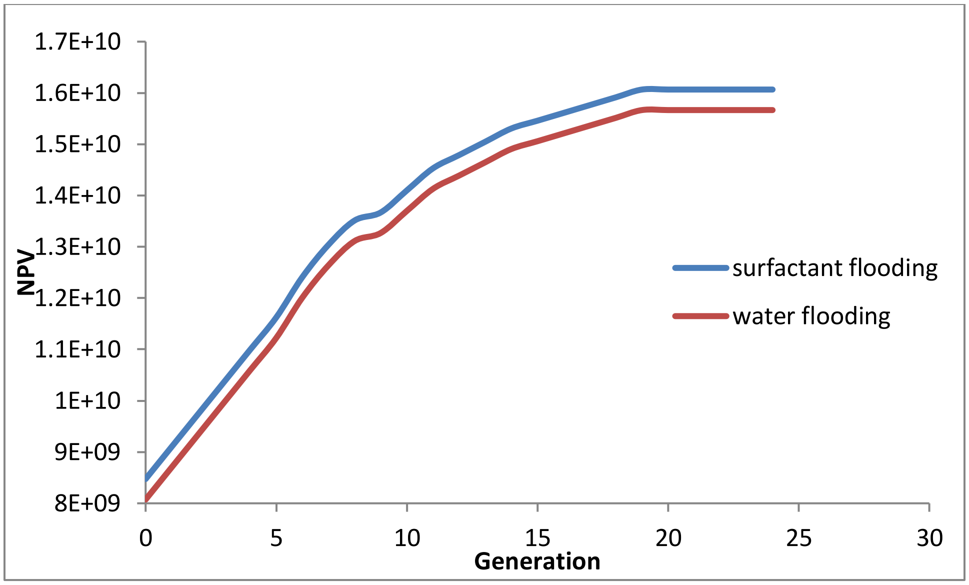


Fig 10. The NPV vs. generation plot for 3 injection wells for the conventional reservoir

In each case, the total time of simulation is *10000* □□□ 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. 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. 11 to Fig. 13.

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* □□□
Injection rate	*400* □□□/□□□
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* □□□
Injection rate	*400* □□□/□□□
Best NPV	$1.3928 \times 10^9 \$$

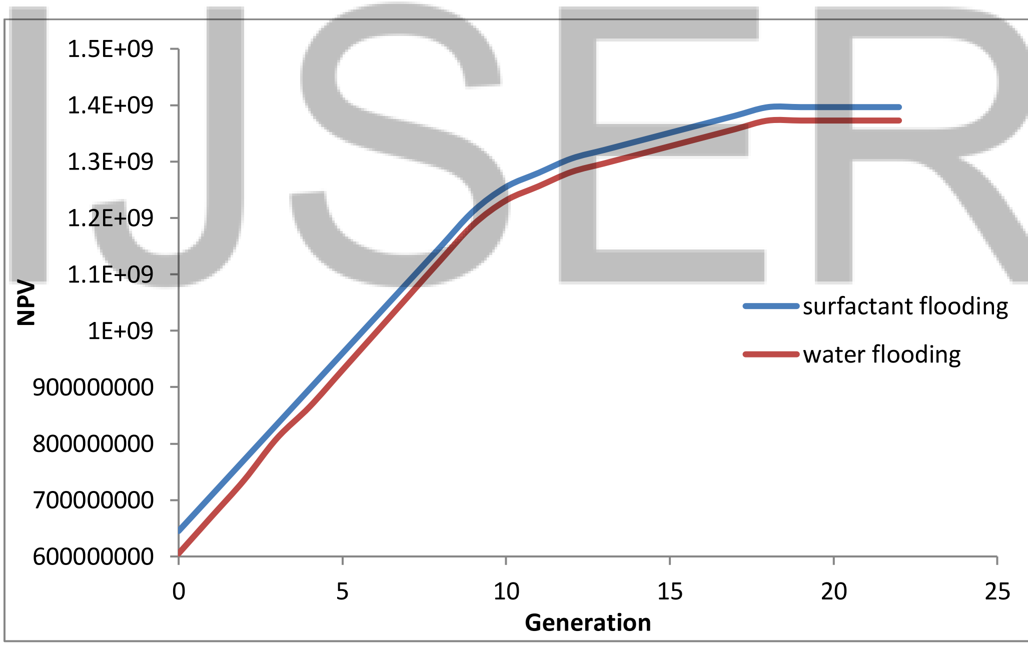


Fig 11. The NPV vs. generation plot for 1 injection well for the fractured reservoir

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 □□□*
Injection rate	*400 □□□/□□□*
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 □□□*
Injection rate	*400 □□□/□□□*
Best NPV	1.4543×10^{9} $

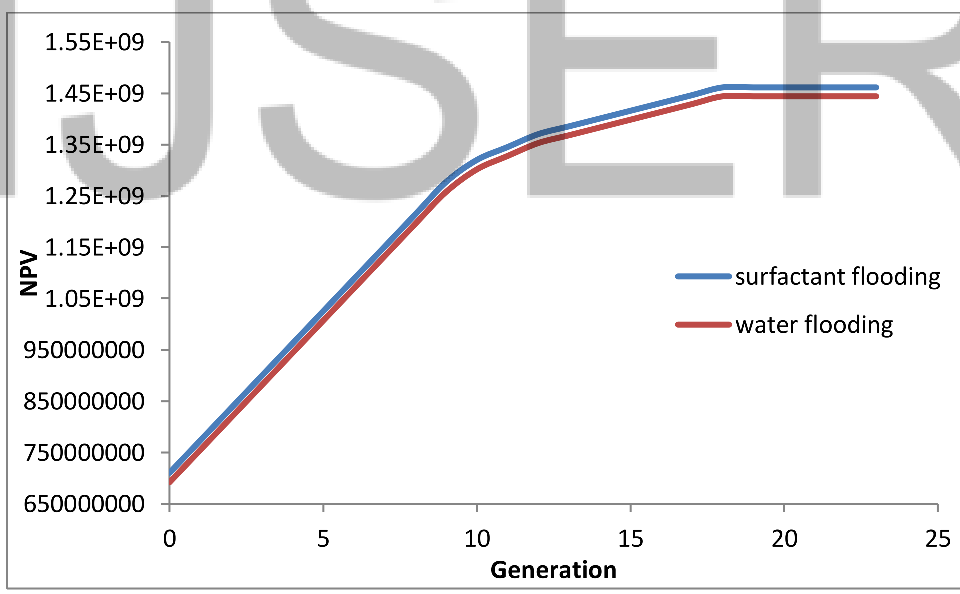


Fig 12. The NPV vs. generation plot for 2 injection wells for the fractured reservoir

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* □□□
Injection rate	*400* □□□/□□□
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* □□□
Injection rate	*400* □□□/□□□
Best NPV	1.5516×10^9 \$

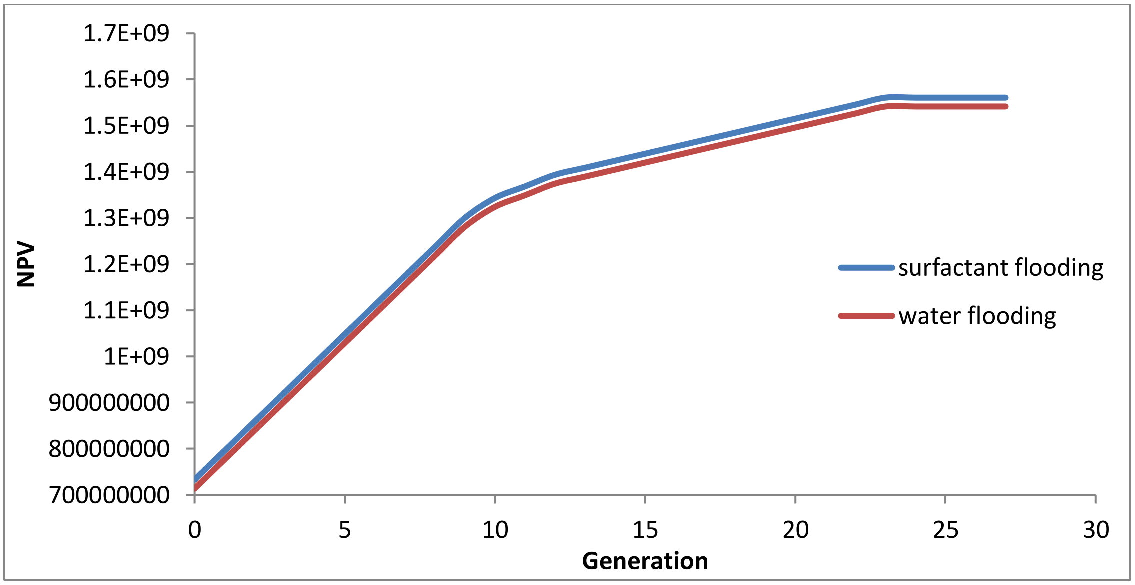


Fig 13. The NPV vs. generation plot for 3 injection wells for the fractured reservoir

The results is similar to the conventional reservoirs. So the more injection time the more economic efficiency. But in this case, the best wells for injection are located at the side of the Reservoir because when we choose the middle wells for injection, 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.

6. Conclusion

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 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. Also we conclude that the surfactant flooding is efficient process in conventional and dual permeability reservoirs and in dual porosity reservoirs, such process is not effective. So before the chemical flooding like surfactant flooding, we must be familiar to type and characteristic of the reservoir

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