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Fluid Injection Optimization Using Modified Global Dynamic Harmony Search

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Abstract

One of the mostly used enhanced oil recovery methods is the injection of water or gas under pressure to maintain or reverse the declining pressure in a reservoir. Several parameters should be optimized in a fluid injection process. The usual optimizing methods evaluate several scenarios to find the best solution. Since it is required to run the reservoir simulator hundreds of times, the process is very time consuming and cumbersome. In this study a new intelligent method of optimization, called "global dynamic harmony search" is used with some modifications in combination with a commercial reservoir simulator (ECLIPSE®) to determine the optimum solution for fluid injection problem unknowns. Net present value (NPV) is used as objective function to be maximized. First a simple homogeneous reservoir model is used for validating the developed method and then the new optimization method is applied to a real model of one of the Iran oil reservoirs. Three strategies, including gas injection, water injection, and well placement are considered. Comparing the values of NPV and field oil efficiency (FOE) of gas injection and water injection strategies, it is concluded that water injection strategy surpasses its rival. Considering water injection to be the base case, a well placement optimization is also done and best locations for water injection wells are proposed. The results show the satisfying performance of the algorithm regarding its low iterations.

Keywords: Harmony Search, Global Dynamic Harmony Search, Well Placement Optimization, Fluid Injection Optimization

1. Introduction

A mature field is the one where production has reached its peak and has started to decline. Mature fields have come into focus in recent years as a consequence of the overall decline of oil reserves. Mature fields account for over 70% of the world's oil and gas production, with many in the secondary or tertiary production phases. The average recovery factors for gas and oil are 70% and only 35% respectively. Even smaller recovery rates are common due to geological characteristics, resource constraints, or operational inefficiencies from old technologies. Increasing ultimate recoveries in these fields, often with reduced resources, is a common dilemma. However, given the vast reserves remaining in these fields, every percentage increase in recovery could generate a two-year global

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supply of hydrocarbons. To enhance the production of mature fields, engineers face challenges such as:

- Identifying potential recoverable fluids;
- Managing cost-effective drilling, completion, and intervention;
- Increasing production;
- Achieving more reservoir exposure through extended drilling;
- Minimizing the unwanted production of sand and water.

One of the mostly used enhanced oil recovery methods is the injection of water or gas under pressure to maintain or reverse the declining pressure in a reservoir. Injecting water to maintain pressure works for a number of reasons. Firstly, water and oil do not mix, which means that the injected water displaces the oil present. Secondly, adding water maintains the pressure, which subsequently keeps the flow.

Water and gas management in oilfields is one of the most challenging problems in oil and gas industries. It is well understood that the presence of water in oil reservoirs can cause tremendous difficulties and increase the complexity of producing oil. Issues include increased lifting costs, increased strain on equipment, and the environmentally safe disposal of the produced contaminated water (although in many cases the produced water is re-injected back into the well for further flooding). In order to increase the recovery and reduce the production cost, the management of water and gas production should be considered in full field studies for depletion planning and field development, from beginning of the production. Considerations for water flooding include reservoir permeability, fluid saturations, heterogeneity, oil viscosity and gravity, reservoir depth and lifting costs, and the availability of a suitable water source (for water injection).

Several parameters should be optimized in a fluid injection process. The usual optimizing methods evaluate several scenarios to find the best solution. Since it is required to run the reservoir simulator hundreds of times, the process is very time consuming and cumbersome.

In this study, a new intelligent method of optimizing, called global dynamic harmony search, is used to find the most suitable solution for a fluid injection problem. This method is modified to have better performance concerning the nature of problem and the fact that running the simulator software is really time consuming. So reducing the number of function evaluations is one of the important factors in this study. Net present value of different strategies is used as the target function. The well location optimization of an inverted five spot water flood process is used for validating the developed method and then the method is applied to one of the major oilfields of Iran.

2. Background of harmony search

In 2001, Geem et al. introduced a new meta-heuristic method named harmony search (HS), which was inspired by musical harmony (Geem et al., 2001). Musical performances seek the best state (fantastic harmony), determined by aesthetic estimation, the same as the optimization algorithms which seek the best state (global optimum-minimum cost or maximum benefit or efficiency), determined by objective function evaluation. Aesthetic estimation is determined by the set of the sounds played by joined instruments, just the same as the objective function evaluation which is determined by the set of the values produced by component variables; the sounds for better aesthetic estimation can be improved through practice after practice just the same as the values for better objective function evaluation which can be improved by iteration by iteration.

The optimization procedure of the harmony search meta-heuristic algorithm consists of five steps as follows (Lee & Geem, 2005):

- Step 1. Initialize the optimization problem and algorithm parameters;
- Step 2. Initialize the harmony memory (HM);
- Step 3. Improvise a new harmony from the HM;
- Step 4. Update the HM;
- Step 5. Repeat Steps 3 and 4 until the termination criterion is satisfied.

The pseudo code of harmony search algorithm is shown in Figure 1.

```
Begin
Objective function f(x), x=(x1, …,xp)T
General initial harmonics (real number arrays)
Define pitch adjusting rate (PAR) and pitch limits
Define harmony memory accepting rate (HMCR)
While (t< Max number of iterations)
        Generate new harmonics by accepting best harmonics
        Adjust pitch to get new harmonics (solutions)
        If (rand >HMCR),
                Choose an existing harmonic randomly
        Else if (rand >PAR),
                Adjust the pitch randomly within a bandwidth
        Else
                Generate new harmonics via randomization
        End if
        Accept the new harmonics (solutions) if better
End While
Find the current best estimates
End
```

Figure 1
Pseudo code of harmony search (Yang 2009)

The harmony search algorithm has been so far applied to various optimization problems. It has been successfully used in many fields (Geem et al., 2001; Lee & Geem, 2005; Omran & Mahdavi, 2008; Geem, 2006; Geem, 2007a; Geem, 2007b).

Since the first presentation of HS, many modifications have been proposed to the HS to reinforce its accuracy and convergence speed. The main drawback of the original HS is that the parameters are set to fixed values, and it is difficult to suggest a value that works well with every optimization problem. Mahdavi et al. (2007) developed the original HS algorithm and proposed the improved harmony search (IHS) (Mahdavi et al., 2007). They used dynamic values for parameters of pitch adjustment rate (PAR) and bandwidth (bw) to overcome the HS drawbacks. Although their suggestion was constructive and improved the HS very well, their work had the drawback of requiring some parameters to be set before the optimization process. Omran and Mahdavi (2008) presented a new modification to HS algorithm named global-best harmony search (GHS) algorithm (Omran & Mahdavi 2008). Their work was just the previous version of HS algorithm, IHS, but with a difference in the improvisation step. Although this variation of HS was valuable, some parameters had to be set before the process. Cobos et al. (2011) presented another method named “global-best harmony search using learnable evolution Models (GHS+LEM)” (Cobos et al., 2011). They used new machine learning techniques to generate new populations along with the Darwinian method, which was used in evolutionary computation and was based on mutation and natural selection. This method still has its own parameters in addition to HS parameters, which should be set before the start of the process.

3. Global dynamic harmony search (GDHS)

In 2012, Khalili et al. presented a new modification to harmony search algorithm with dynamic parameters (Khalili et al., n.d.). They suggested that the parameters of HMCR and PAR should have a waving behavior, starting with a small value going up to 1 and again coming back to the start point. This behavior has a great influence on the results. These fluctuations in HMCR and PAR make the algorithm to generate and pick values in certain times. Also, they proposed a method to reduce the exploration domain as reaching the final solution.

The HMCR and PAR parameters proposed by them are as follow:

$$\mathrm{HMCR} = 0.9+0.2\times\sqrt{\frac{iteration\text{-}1}{Max_{\mathrm{imp}}\text{-}1}\times\left(1-\frac{iteration\text{-}1}{Max_{\mathrm{imp}}\text{-}1}\right)} \tag{1}$$

$$\mathrm{PAR} = 0.85+0.3\times\sqrt{\frac{iteration\text{-}1}{Max_{\mathrm{imp}}\text{-}1}\times\left(1-\frac{iteration\text{-}1}{Max_{\mathrm{imp}}\text{-}1}\right)} \tag{2}$$

The improvisation procedure of GDHS is shown in following algorithm.

for each *"i∈[1,maximum improvisation]"* ***do***
  $bw_{max}=\frac{\Delta(\text{upper and lower limits})}{bw_{den}}$
  $U^{HM}=max\left(max\left(HM(:,1:ND)\right)\right)$
  $L^{HM}=min\left(min\left(HM(:,1:ND)\right)\right)$
  $U^{new}=U^{HM}+bw_{max}$
  $L^{new}=L^{HM}\text{-}bw_{max}$
  New_limit= [L^{new} U^{new}];
  if *U^{new} ≤Max.Allowed Limit,* *%Control the new limits not to exceed the original limits*
    Max. Limit=U^{new}
  end_if
  if *L^{new} ≥Min.Allowed Limit*
    Min. Limit=L^{new}
  end_if
done
Limit=New_limit;
  $\mathrm{HMCR}=0.9+0.2\times\sqrt{\frac{iteration\text{-}1}{Max_{\mathrm{imp}}\text{-}1}\times\left(1-\frac{iteration\text{-}1}{Max_{\mathrm{imp}}\text{-}1}\right)}$
  $\mathrm{PAR}=0.85+0.3\times\sqrt{\frac{iteration\text{-}1}{Max_{\mathrm{imp}}\text{-}1}\times\left(1-\frac{iteration\text{-}1}{Max_{\mathrm{imp}}\text{-}1}\right)}$
for each *i∈[1 ND]* ***do***
  if *rand< HMCR* ***then*** */*memory consideration*/*
    begin
      $x_i'=x_i^j$*, where j~U (1,…, HMS)*
      if *rand ≤ PAR* ***then*** */*pitch adjustment*/*
$\mathrm{C}=\left(1+\left(\mathrm{HMS}\text{-}j\right)\right)\times\left(1-\frac{iteration\text{-}1}{Max_{\mathrm{imp}}\text{-}1}\right)\times\mathrm{HMS}$ $x_i'=x_i'\pm bw\times C$
        if *x_i' is not in the range of limits, correct it*
          $x_i'=x_i'\mp bw\times C$
        end_if
      end_if
    end
  else */*random selection*/*
    $x_i'=L+rand\times(U\text{-}L)$
  end_if
done

Figure 2
Improvisation step in GDHS algorithm (Khalili et al., n.d.)

4. Modified GDHS

In this study, the GDHS algorithm is changed in a manner which can handle petroleum engineering kind of problems in a better way considering the importance of the convergence speed. In the proposed method, the same HMCR and PAR equations in GDHS algorithm are used, but the coefficient parameter is eliminated to reduce the algorithm complexity. The denominator coefficient of the maximum bandwidth is changed to the following form to increase the maximum bandwidth (to prevent sudden domain changes):

$$bw_{\mathrm{den}}=4\times\mathrm{abs}(1+\log_{10}(U^{\mathrm{original}}-L^{\mathrm{original}})) \tag{3}$$

$$\mathrm{bw}_{\max}=\frac{\Delta(\text{upper and lower limits})}{bw_{\mathrm{den}}} \tag{4}$$

Thus the bandwidth formula will be:

$$\mathrm{bw}=bw_{\max}\times e^{\left((\mathrm{Ln}\,(0.001))\times\left(\frac{iteration-1}{Max_{\mathrm{imp}}-1}\right)\right)} \tag{5}$$

This is used in pitch adjustment step:

$$x_j^{\mathrm{new}}=x_j^{\mathrm{old}}\pm k\times bw,\ \text{where } k\sim U(-1,1) \tag{6}$$

The main change in the modified version of GDHS is to segregate the domain in a way which divides it into three or four parts. In each part, the modified GDHS algorithm is run and a premature optimization is done. After that, all the solution vectors found in each part are combined and a harmony memory of size HMS is chosen from the best solutions. Now, a full optimization process is done on overall area with the new HM. This helps a deep investigation of area ensuring that the entire domain has been searched. A schematic of this step is shown in Figure 3.

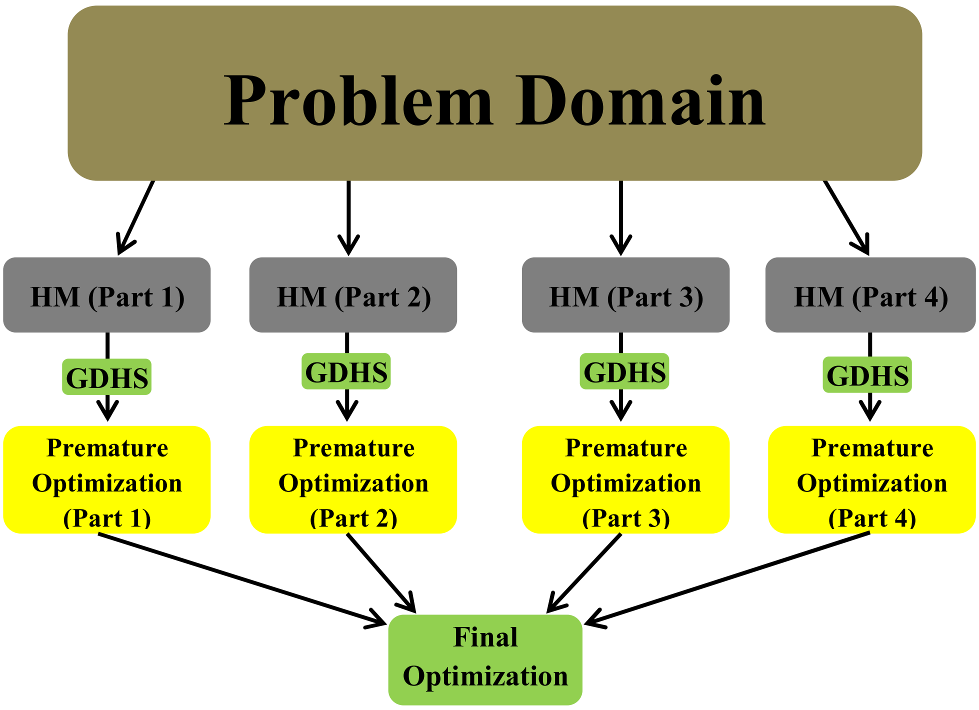

Figure 3
Optimization procedure in modified GDHS

5. Objective function

One of the input parameters that user has to define prior to submitting an optimization run is the type of objective function to be optimized. Two types of objective functions are available in the formulation of this work, namely cumulative production and NPV. After each individual is simulated, the calculation of each objective function is possible by reading the simulation output file. While cumulative oil production represents a single value, the total oil volume by the end of simulation, NPV, takes more of the economics of the project into consideration. NPV is calculated based on a fixed annual effective discount rate as reads (Abukhamsin, 2009):

$$\mathrm{NPV}=\left(\sum_{n=1}^{Y}\sum_{p=o,g,w}\frac{1}{(1+i)^n}Q_p^n.C_p\right)-C_d \tag{7}$$

where, Q_p^n indicates the production rate of phase p during the year n; C_p denotes the unit profit or cost associated with this phase; i is the annual percentage rate (APR) and Y stands for the total number of discount years; C_d is drilling and completion cost determined by:

$$\mathrm{C_d}=\sum_{i=1}^{well\ count}C_{\mathrm{CAPEX}}+L_{\mathrm{tot,i}}C_{\mathrm{drill}}+(Lat_{\mathrm{count}}.C_{\mathrm{mill}}) \tag{8}$$

where, C_{CAPEX} is a capital expenditure cost per well including platform cost and the cost of drilling to the top of the reservoir; C_{drill} represents the unit drilling cost per feet and C_{mill} is the cost of milling a new junction.

Since, in case of study, it is assumed that no new well is drilled/completed and that all wells are producing/injecting for all the optimization strategies, the C_d can be neglected. In addition, because only the cumulative production and injection have been read from the ECLIPSE output file, it is assumed that the annual discount rate is zero (since our purpose is to compare the different values of NPV in a single strategy, this assumption is not crucially harmful). With the assumption of zero discount rate, the annual production is replaced with cumulative production at the end of optimization period. Hence the NPV is reduced to the following form:

$$\mathrm{NPV}=\left(\sum_{n=1}^{Y}\sum_{p=o,g,w}Q_p^n.C_p\right) \tag{9}$$

This equation can be written as:

$$NPV\,(T)=R_oQ_o\,(T)+R_gQ_g\,(T)-C_{wp}Q_{wp}\,(T)-C_{wi}Q_{wi}\,(T)-C_{gi}Q_{gi}\,(T) \tag{10}$$

where, NPV (T) is the net present value over the period of time T. R_o and R_g are the revenue from selling oil and gas; C_{wp}, C_{wi}, and C_{gi} are the cost of handling produced water and the cost of water injection, and the cost of gas injection respectively; Q_o, Q_g, Q_{wp}, Q_{wi}, and Q_{gi} are the cumulative oil production, gas production, water production, water injection, and gas injection respectively obtained from the reservoir simulator output. The NPV values presented throughout this study are non-referable and are only used for comparison between different cases.

The economical parameters used to calculate NPV for problems in this project are shown in Table 1. These values are obtained from NISOC (National Iranian South Oilfields Company) economic studies.

6. Application to a synthetic reservoir model

To test the model, a synthetic reservoir model is simulated using ECLIPSE100 reservoir simulator. The case being studied is an inverted five-spot pattern water flood process including four oil production wells located at the four corners of the reservoir; it is tried to find the best location for a water injection well. The schematic of the reservoir model is shown in Figure 4 and the properties of the reservoir are summarized in Table 2. Moreover, the values used in the modified global dynamic harmony search algorithm for this case are shown in Table 3.

Table 1
Economic parameters used in the NPV calculations

Economic Parameter	Value	Unit
Oil selling price	90	\$/STB
Gas selling price	3000	\$/MMSCF
Gas injection cost	3700	\$/MMSCF
Water production cost	7	\$/MSTB
Water injection cost	7	\$/MSTB

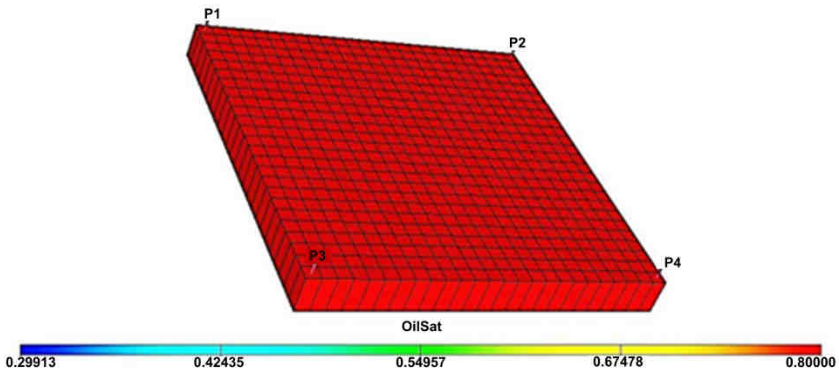

Figure 4
Reservoir model of inverted five-spot pattern

Table 2
Inverted five-spot reservoir model properties

Property	Value	Property	Value
X dimension	25	Porosity (Fraction)	0.2
Y dimension	25	Permeability (md)	50
Z dimension	1	S_{wi}	0.2
Dx (ft)	20	S_{or}	0.1778
Dy (ft)	20	Rock compressibility	4×10^{-6}
Dz (ft)	50	Oil density (lb./ft3)	55
Top (ft)	5000	Water density (lb./ft3)	62.43
Well bore diameter (ft)	1	Injection /Production Period (Days)	150
Active phases	Oil, water		

The case being studied is an inverted five-spot water injection problem that has dimensions of 25×25×1 cells in x, y, and z directions respectively with a sum of 625 cells. From petroleum engineering point of view, it is known that the best location of an injection well in an inverted five-spot pattern water flood project is the center of the reservoir, namely at (13, 13) in this example. The graph of NPV versus generation is shown in Figure 5.

Table 3
Modified GDHS parameters for inverted five-spot reservoir model

Harmony Memory	Number of Grids	HMS	Maximum Improvisation	Number of Function Evaluations
Part 1	144	3	1	4
Part 2	156	3	1	4
Part 3	156	3	1	4
Part 4	169	3	1	4
HM (Final)	625	6	24	24
			Sum	40

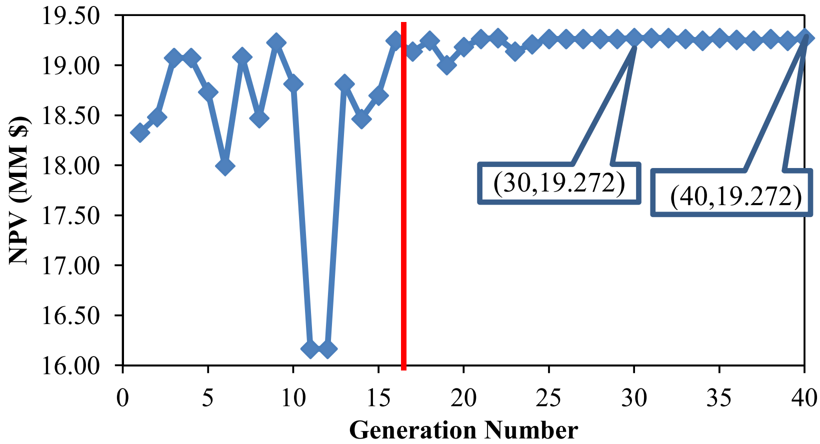

Figure 5
NPV versus generationnumber for inverted five-spot patterns

The points on the left side of the vertical line (iterations less than 16) belong to the premature optimization step. From the NPV graph, it is seen that after 16 generations (40% of total generations), the algorithm is very close to the correct solution; however, to find the exact position of the injection well, which has the largest NPV, it takes 24 more iterations. Although by domain dividing some generations might be lost, which may results in looking for solution in wrong sections, this is very valuable because by taking 40% of the overall generations in the divided sections of the domain a solution is obtained that is more than 95% close to the actual solution (the values may differ in different problems). The algorithm finds the best location after 30 generations, which have the largest NPV of $19.2724 million, and this solution has been repeated at the last generation (number 40). For this case, the stopping criterion is to reach the maximum number of generations.

7. Reservoir and model description

The case being studied here is one of the major oil reservoirs in Iran and is located in the southwest of Iran; let's call it reservoir "A". This reservoir was explored in 1968. It has dimensions of 60 km length and 5 km width. By the year of 2010, there were 16 production wells in this reservoir. This reservoir has an asymmetric anticline structure and its crest is 3093 meters of subsea and it has a closure of 1307 meters.

Although there are minor fractures in the reservoir structure, the reservoir matrix has a great share in production and it is affected by dolomitization and recrystallization phenomena. Furthermore, in some parts, secondary porosity in the form of moldic and vuggy porosity contributes to production. Generally, the reservoir has a porosity of 10% and a permeability of 0.5 millidarcy (matrix permeability). In some geological zones, low porosity (less than 5%) with different permeabilities are representative of fractures in the reservoir. The initial reservoir pressure was about 6000 psi and it is currently reduced to about 4700 psi. Until the time of study, a cumulative of 16 MM cubic meters (or 100 MM STB) of oil is produced from this reservoir.

The model used in this study has grid blocks with dimensions of (42, 101, 72) in x, y, and z directions respectively. At the start of the optimization (2010), the number of wells is increased to 49 production wells. For the optimization, three strategies, including gas injection, water injection, and well placement are considered. In all the strategies, there are two injector wells. The reservoir is assumed to be no flow boundary. The reservoir is simulated using black oil reservoir simulator (ECLIPSE100). Oil, water, and gas exist as three phases in the reservoir. As it is seen from the porosity and permeability figures, the reservoir is completely heterogeneous; this makes the reservoir a good choice for the optimization of well location and water/gas injection. Since the values of well coordinates are changed from their real values to the corresponding simulator I, J, and K values, completions are assumed to be at the center of the grid blocks.

8. Results and discussion

8.1. Strategy 1: gas injection optimization

One of the main problems in fluid injection is that how much of a fluid should be injected into a reservoir to have the best recovery. This factor is called voidage replacement ratio, and is defined as the proportion of the injected fluid to the reservoir volume (voidage). This value is used by the keyword of "GCONINJE" in ECLIPSE100 software. In this section, we are trying to find the optimum voidage replacement ratio by gas injection in reservoir "A", which results in the maximum NPV over a 90-year period up to the year of 2100. The voidage replacement values in this strategy vary from 0.5 to 3 times of the reservoir volume. The economical parameters used to calculate NPV are already given in Table 1. Since, in this example, there is no water injection, the equation for NPV (Equation 10) is reduced to the following form:

$$NPV(T) = R_o Q_o(T) + R_g Q_g(T) - C_{wp} Q_{wp}(T) - C_{gi} Q_{gi}(T) \quad (11)$$

As discussed before, for optimization, the range of possible values for voidage replacement is divided into three equal parts and a premature optimization is done on each part. Afterwards, the best solutions all over the domain are gathered together and only the best ones with the size of final harmony memory are selected for the full optimization process. Since the gas injection problem under study takes too much time (more than 8 hours for each run), the maximum number of function evaluations is set to 30 (including initial harmony memory, premature optimization, and final optimization), which gives a balance of time and accuracy. An important issue in this strategy (and the strategy of water injection) that must be considered is that, since there is only one unknown parameter, the value of pitch adjustment rate is set to 1. This is necessary to prevent the algorithm to repeat the same values that already exist in the harmony memory. The parameters used in the modified GDHS algorithm are shown in Table 4.

Overlaps of 25% from upper and lower limits are considered to take more control of marginal points and not to lose any probable solution near the margins of the different parts.

Figure 6 shows NPV versus generations. From this figure, the modified GDHS method has found the optimum value of voidage replacement after 28 generations. Figure 7 illustrates NPV versus voidage replacement ratio.

Table 4
Modified GDHS parameters used in the gas injection optimization

Harmony Memory	Range	HMS	Maximum Improvisation	Number of Function Evaluations
Part 1	0.5-1.5	5	3	8
Part 2	1.25-2.25	5	3	8
Part 3	2-3	5	3	8
HM (Final)	0.5-3	5	6	6
			Sum	30

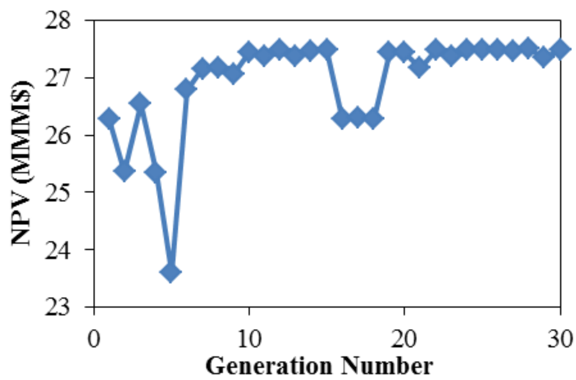

Figure 6
NPV (Billion $) versus generation number in the gas injection optimization

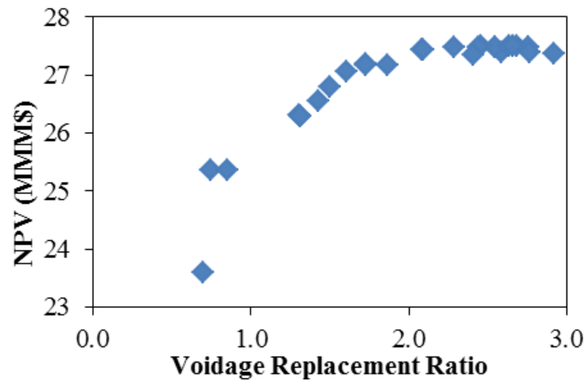

Figure 7
NPV versus voidage replacement ratio in the gas injection optimization

Since the actual reservoir model is used in this approach and the reservoir model should be run for each objective function evaluation, the optimization took 240 hours (8 hours for each run). The cause of each run of simulation taking such long time is that we use the whole of the reservoir (not a section) and also there are three phases of gas/water/oil at the same time; therefore, the matrix of unknowns takes too much time to be solved by the simulator. The optimum voidage replacement ratio obtained by the algorithm is 2.6825, which gives an NPV of $27.500 billion and an FOE of 9.440. As it is seen from Figure 7, the new method of optimization presented here almost supports all the area of the domain and the reservoir behavior can easily be predicted.

8.2. Strategy 2: water injection optimization

In the previous section, a gas injection problem was optimized. In this section, the reservoir is to be optimized with water being injected instead of gas. Again it is tried to find the maximum NPV over a 90-year period up to the year of 2100. The voidage replacement values vary from 0.5 to 3 times of the reservoir volume. The economical parameters used to calculate NPV are already given in Table 4. Since, in this example, there is no gas injection, the equation for NPV (Equation 10) is reduced to the following form:

$$NPV\,(T) = R_oQ_o\,(T) + R_gQ_g\,(T) - C_{wp}Q_{wp}\,(T) - C_{wi}Q_{wi}\,(T) \qquad (12)$$

The range of possible values for voidage replacement is divided into three equal parts and a premature optimization is done on each part. Afterwards, the best solutions all over the domain are gathered together and only the best ones with the size of final harmony memory are selected for the full optimization process. The maximum number of optimizations is set to 50 (including initial harmony memory, premature optimization, and final optimization), which gives a balance of time and accuracy. As discussed before, in the strategy of gas injection, in this case, PAR is set to 1 to prevent repetition in harmony memory calculations. The parameters used in the modified GDHS algorithm are shown in Table 5.

Table 5
Modified GDHS parameters used in the water injection optimization

Harmony Memory	Range	HMS	Maximum Improvisation	Number of Function Evaluations
Part 1	0.5-1.5	5	3	8
Part 2	1.25-2.25	5	3	8
Part 3	2-3	5	3	8
HM (Final)	0.5-3	5	26	26
			Sum	50

Figure 8 shows NPV versus generations. From this figure, the modified GDHS method has found the optimum value of voidage replacement after 44 generations. Furthermore, a graph of NPV versus voidage replacement ratio is shown in Figure 9.

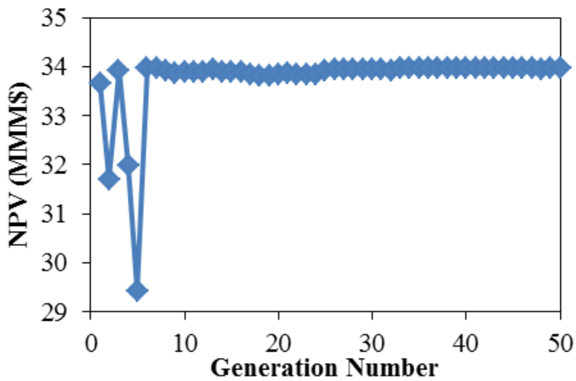

Figure 8
NPV (Billion $) versus generation number in the water injection optimization

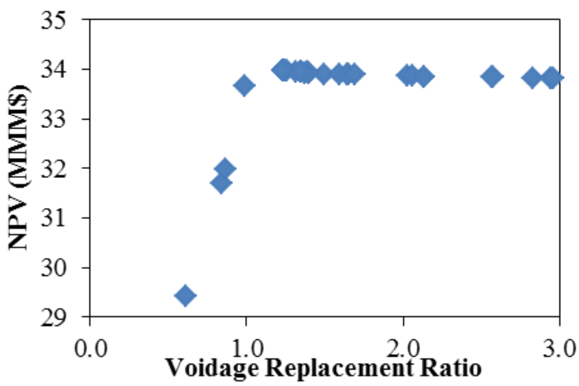

Figure 9
NPV versus voidage replacement ratio in the water injection optimization

Since the actual reservoir model is used in this approach and the reservoir model should be run for each objective function evaluation, the optimization took 44.1 hours (53 minutes for each run). The optimum voidage replacement ratio obtained by the algorithm is 1.2323, which gives an NPV of $33.979 billion and an FOE of 10.787. As it is seen from Figure 9, the new method of optimization presented here almost supports all the area of the domain; the reservoir behavior can easily be predicted and the concentration of the data is around the best answer. Figure 10 shows a comparison of the two optimization strategies, namely gas injection and water injection. It is obvious that water injection strategy gives the higher values of NPV and FOE with a lower voidage replacement ratio. From these findings, the water injection strategy is used in the well placement optimization problem to get the maximum NPV and FOE.

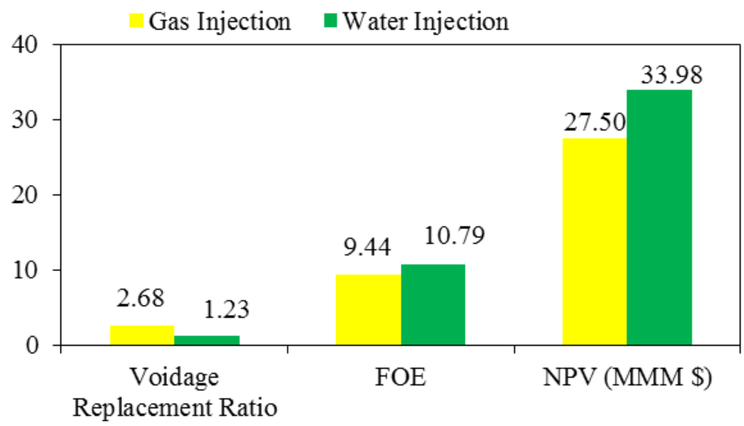

Figure 10
Comparison of gas injection and water injection

In the cases of gas and water injection, there is only one unknown parameter. In such cases, it seems more convenient to use a regression, instead of intelligent optimization, to obtain the maximum and minimum values; but, there are two main advantages of using harmony search optimization instead of regression.

Firstly, in regression, all runs have to be sent to the simulator (30 runs for gas and50 runs for water) in advance and then a curve should be matched on the data; using the fitted curve, the optimum point is calculated. However, in harmony search algorithm, the optimizer runs the simulator for initial memory and then it proposes the next value for the simulator by comparing the output of the simulator with the harmony memory; it will be updated after each generation. Secondly, there is no assurance that the reservoir behavior follows a specific trend which could be predicted by a regression.

8.3. Strategy 3: well placement optimization

Optimizing well locations is challenging due to large solution space, expensive and time consuming simulations, and the number of variables. Each well has at least 3 unknown parameters; x, y, and z directions include 2 variables of top and bottom positions for well completion). In oil production, the reservoir is often subjected to different types of geological uncertainties. The optimization of well location under uncertainty becomes more challenging since it involves the variability of simulation observations.

Well placement is the combination of the right technology and expert log analysis to complement the drilling process to position wells that intersect the best pay zones efficiently, safely, and on time. This combination helps maximize hydrocarbon recovery, postpone water production, and extend well life. Accurate well placement improves the long-term and short-term performance of the wells.

In the previous sections, gas and water injection problems were optimized and it was found that water injection strategy was more valuable against gas injection, comparing their NPV and FOE values. Now the optimum value for voidage replacement ratio by water injection is used and the best injector well locations which lead to the maximum NPV over a 90-year period up to the year of 2100 are found. The economical parameters used to calculate NPV are already given in Table 1. In this example, there is no gas injection, so Equation 10 can be used for NPV calculation:

$$NPV\,(T) = R_o Q_o\,(T) + R_g Q_g\,(T) - C_{wp} Q_{wp}\,(T) - C_{wi} Q_{wi}\,(T) \qquad (10)$$

The reservoir model is a dual porosity model and it has grid blocks with the dimensions of (42, 101, and 72) in x, y, and z directions respectively; thus it totally has 42×101×72=305,424 grids. The z direction is divided into two portions; the top 36 layers are reserved for matrix and the lower 36 layers are reserved for fracture; knowing this, the injector wells are drilled into fracture grid blocks. Hence the number of grids is reduced to 305,424÷2=152,712. In z direction, only grids 38 to 67 are used in the optimization; therefore, the number of girds is reduced to 42×101×30=127,260. The marginal grids that were difficult to handle in the algorithm and also the grids that were poor in porosity and permeability were neglected in the optimization. Finally, 28,170 grids were used for the well location search. There are two water injector wells and each well has three parameters to be optimized, including x and y locations (i,j) as well as top locations for well completion (k_1); the bottom completion point is assumed to be two grid blocks lower than the top completion point ($k_2= k_1+2$). These parameters are used in the keywords of WELSPECS and COMPDAT by the ECLIPSE software. The parameters used in the modified GDHS algorithm are shown in Table 6.

Table 6

Modified GDHS parameters used in the well placement optimization

Harmony Memory	Number of Grids	HMS	Maximum Improvisation	Number of Function Evaluations
Part 1	150	3	3	6
Part 2	162	4	4	8
Part 3	289	6	6	12
Part 4	338	7	7	14
HM (Final)	939	7	60	60
			Sum	100

The entire area of the reservoir is divided into four parts and a premature optimization is done on each part. After that, the best solutions all over the domain are gathered together and only the best ones with the size of final harmony memory are selected for the full optimization process. The maximum number of optimizations is set to 100 (including initial harmony memory, premature optimization, and final optimization), which gives a balance of time and accuracy.

Figure 11 shows the results for NPV versus generations. From this figure, the modified GDHS method has found the optimum values for well locations after 99 generations. Additionally, a graph of field oil efficiency (FOE) versus generations is shown in Figure 12. As it is seen from this figure, FOE follows the same behavior of NPV.

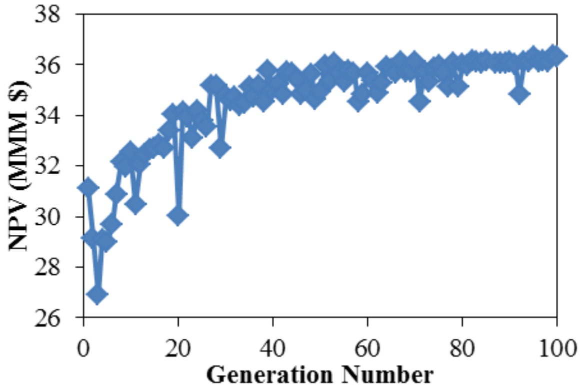

Figure 11

NPV (billion $) versus generation number in the well placement optimization

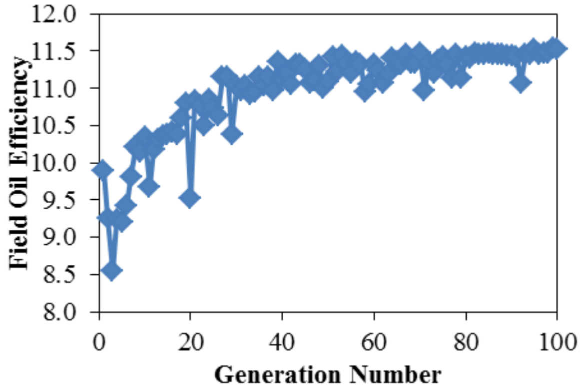

Figure 12

Field oil efficiency versus generation number in the well placement optimization

Since the actual reservoir model is used in this approach and the reservoir model should be run for each objective function evaluation, the optimization took 6088 minutes or about 101.4 hours (about 61 minutes for each run). The optimum well locations obtained by the algorithm are well 1(26, 64, 39) and well 2 (27, 48, 38) and give an NPV of \$36.369 billion and an FOE of 11.546.
The comparison of the aforementioned sections (gas injection, water injection, and well placement) is shown in Figure 13. This figure shows the comparison of the different optimization strategies used for the reservoir "A". It is obvious from this figure that the water injection with well placement strategy is the best combination.

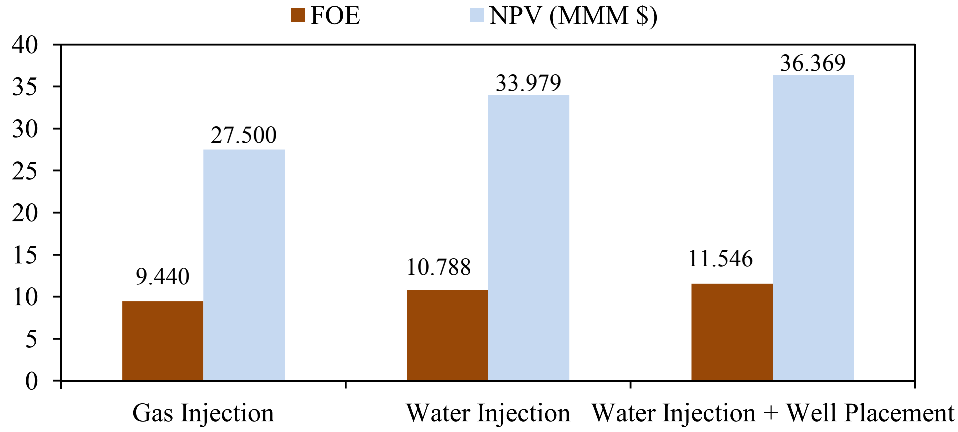

Figure 13
NPV and FOE for different optimization scenarios in reservoir "A"

Figures 14 through 17 show the water saturation of the reservoir matrix and fracture at the start of the injection project (2010) and at the end of the injection (2100). Because of low values for permeability and porosity of the matrices, until the year of 2100, the production is mostly from fractures and only a little portion of production is obtained from matrices. The locations of the injecting wells are shown in Figure 17.

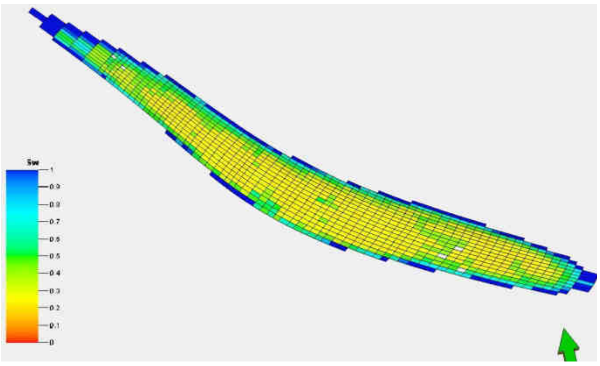

Figure 14
Water saturation of matrix in the year of 2010 (start of water injection)

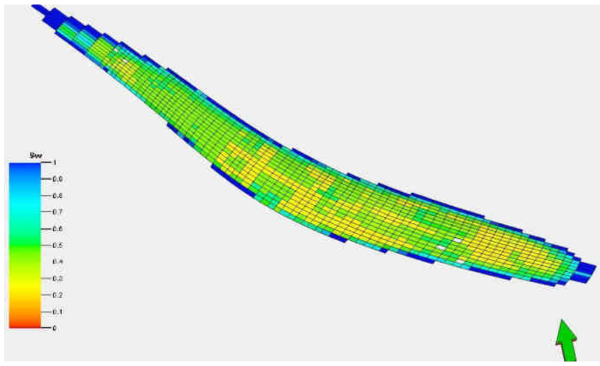

Figure 15
Water saturation of matrix in the year of 2100 (end of water injection)

Dividing the search area into a few regions helped to obtain a fast convergence in which more than 80% of the searching process has been done in this period, and then in the main optimization period the accuracy of the results has been improved. Although there were repeated solutions in the process, which slowed down the convergence, those repetitions were inevitable in any random search-based algorithm. The maximum number of improvisations should be guessed considering the size of the area being searched.

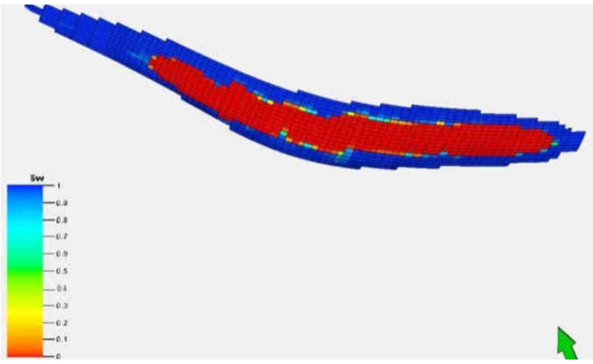

Figure 16
Water saturation of fracture in the year of 2010 (start of water injection)

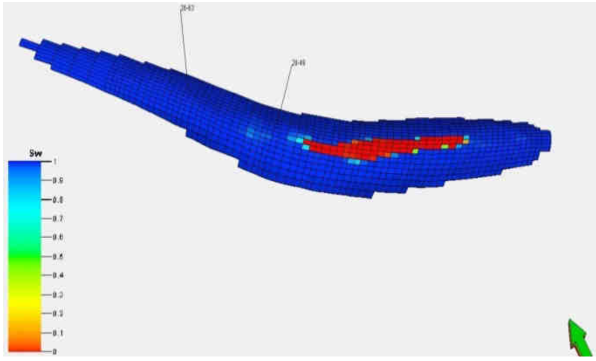

Figure 17
Water saturation of fracture in the year of 2100 (end of water injection)

9. Conclusions

Based on the results obtained, the following conclusions can be drawn:

1. The algorithm of global dynamic harmony search has been modified in a manner which makes it more suitable for petroleum engineering kind of problems by focusing on lowering the number of function evaluations which require heavy simulator run times. The method was applied to a well-known benchmark problem in petroleum engineering optimizations, i.e. inverted five-spot water injection problem, and the results were satisfying;
2. The first strategy was to optimize a gas injection problem. The optimum voidage replacement ratio from the optimization was 2.6825 which resulted in an NPV of $27.500 billion and an FOE of 9.440;
3. The second strategy was a water injection problem. The optimum voidage replacement ratio from the optimization was 1.2323 which resulted in an NPV of $33.979 billion and an FOE of 10.787;
4. The third, and final, strategy was well placement optimization problem. The optimum well locations from the optimization were well 1 (26, 64, 39) and well 2 (27, 48, 38), which resulted in an NPV of $36.369 billion and an FOE of 11.546;
5. The results showed the high performance of the modified global dynamic harmony search algorithm, and comparing the results with the values obtained by reservoir engineers at the NISOC verified the accuracy and usefulness of the proposed method;
6. Due to its many advantages, including its simplicity and easy implementation, the global dynamic harmony search algorithm can widely be used in the fields such as function optimization, industrial optimization problems, and so on; GDHS is based on the intelligence. It can be applied to both scientific research and engineering applications;
7. The calculation in GDHS is very simple; in comparison with the other developing calculations, it has lower complexity and provides more investigation into the domain.

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Nomenclature

Bw	: Bandwidth
C	: Cost
FOE	: Field oil efficiency
HM	: Harmony memory
HMCR	: Harmony memory consideration rate
HMS	: Harmony memory size
ND	: Number of dimensions (or variables)
NPV	: Net present value
PAR	: Pitch adjusting rate
Q	: Production or injection rate
R	: Revenue
rand	: Random number
S_{wi}	: Irreducible water saturation
S_{or}	: Residual oil saturation
X	: Variable

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