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Co-optimization of carbon dioxide storage and enhanced oil recovery in oil reservoirs using a multi-objective genetic algorithm (NSGA-II)

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Abstract: Climate researchers have observed that the carbon dioxide (CO_2) concentration in the atmosphere have been growing significantly over the past century. CO_2 from energy represents about 75% of the greenhouse gas (GHG) emissions for Annex B (Developed) countries, and over 60% of global emissions. Because of impermeable cap rocks hydrocarbon reservoirs are able to sequester CO_2. In addition, due to high-demand for oil worldwide, injection of CO_2 is a useful way to enhance oil production. Hence, applying an efficient method to co-optimize CO_2 storage and oil production is vital. Lack of suitable optimization techniques in the past led most multi-objective optimization problems to be tackled in the same way as a single objective optimization issue. However, there are some basic differences between the multi and single objective optimization methods. In this study, by using a non-dominated sorting genetic algorithm (NSGA-II) for an oil reservoir, some appropriate scenarios are proposed based on simultaneous gas storage and enhanced oil recovery optimization. The advantages of this method allow us to amend production scenarios after implementing the optimization process, by regarding the variation of economic parameters such as oil price and CO_2 tax. This leads to reduced risks and time duration of making new decisions based on upcoming situations.

Key words: Greenhouse gas emission, carbon dioxide, enhanced oil recovery, multi-objective optimization, decision making

1 Introduction

The CO_2 concentration trend mostly reflects energy-related activities that, over the past decade, are determined by economic growth, generally in developing countries. The 2012 CO_2 concentration of 394 ppm is about 40% higher than that in the mid-1800s, with an average growth of two ppm/year in the last ten years (Olivier and Muntean, 2013). Despite the growth of non-fossil energy, considered as non-emission, the share of fossil fuels in the worldwide energy supply is almost unchanged over the past 40 years. Climate researchers have found that CO_2 concentrations in the atmosphere have been growing significantly over the past century, compared to the rather steady level of the pre-industrial period (Van der Hoeven, 2013). The International Panel on Climate Change (IPCC) predicts that the CO_2 concentration in the atmosphere may reach 570 ppm by the year 2100, resulting in a rise of mean global temperature and an increase in mean sea level (Javaheri et al, 2009; U S Environmental Protection Agency, 2009).

The Kyoto Protocol of the United Nations Framework Convention on Climate change called for developed countries to reduce emissions of greenhouse gases (GHG) by average of 5.2%, below the 1990 levels by 2008 to 2012. Since clients are interested in saving money, any emission reduction option, such as underground storage that costs less than the tax that would otherwise be paid, will be adopted (McKitrick, 2013).

Geological CO_2 storage as the only effective option to mitigate CO_2 emissions has been considered since 1990s and has been implemented in large scale for the first time in Norway. The Sleipner project is the first commercial CO_2 injection into a deep saline aquifer (US Department of Energy, 2010). Because of impermeable cap rocks, hydrocarbon reservoirs have proper conditions for storage of CO_2. On the other hand, injection of CO_2 is implemented practically to improve oil recovery, and it is more beneficial in oil reservoirs than in gas ones. The main mechanisms in CO_2 enhanced oil recovery (CO_2 EOR) are: decreasing oil-water interfacial tension and CO_2-oil surface tension; dissolving CO_2 in the oil phase; evaporation of intermediate oil components; decrease in in-situ oil viscosity and density; improvement of reservoir permeability and pressure control in the near production well zone. The first commercial CO_2 injection was accomplished in 1972 by Chevron Company in

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Texas, US (Rebscher and Oldenburg, 2005; US Department of Energy, 2010). There are basic differences between enhanced oil recovery with and without CO_2 sequestration. The purpose of CO_2-EOR process is improvement of total oil production per minimum CO_2 injection and the cost of CO_2 capture has to be considered. Simultaneous CO_2-EOR and sequestration could lead to maximization of both total oil production and CO_2 injected volume. Features that should be taken into account for simultaneous CO_2-EOR and sequestration are reservoir depth, oil density, storage capacity, in-situ oil and water volume and reservoir thickness (Ghomian, 2008). Current CO_2 use for EOR ranges between 65 million tons to 72 million tons per year. The volume of CO_2 that could be captured and sequestered from industrial facilities and power plants to support next generation EOR could be 20-45 billion metric tons. This is equal to the total U.S. CO_2 production from fossil fuel electricity generation for 10 to 20 years (National Enhanced Oil Recovery Initiative Report, 2012). At present, eight large-scale CCS (Carbon Capture and Storage) projects are sequestering about 23 million tons of CO_2 per year, globally. With nine projects currently under construction, the amount of stored CO_2 could increase to 37 million tons annually by 2015. The project, which is planned to start in 2015 with the capture of about 2.6 million tons of CO_2, annually, is located at the newly built North West Sturgeon refinery in Canada, where the CO_2 will be sold for enhanced oil recovery (Segura et al, 2013).

Production of oil from some Iranian reservoirs is not economical. For instance, onshore field production decreases by about 10% every year (Soltanieh et al, 2009). So, to enhance oil production secondary and tertiary recovery processes are recommended. By considering the extreme and giant sources of natural gas in Iran, some experts believe that the injection of natural gas could be efficient. However, because of high domestic consumption of natural gas in Iran and the worldwide demand for gas, injection of natural gas is not reasonable. On the other hand, CO_2 emission in Iran has significiently increased from 41.7 million tons in 1971 to 521 million tons in 2011 (Van der Hoeven, 2013). So, CO_2 can be used as a substituted gas for natural gas in EOR with the advantages of air pollution reduction.

There are some prohibitive rules such as CO_2 emission tax that can affect development of CO_2 storage. Nowadays, this type of tax has been increased to 700 $ per ton in some countries. The Clean Development Mechanism (CDM) provides a route for developing/underdeveloped countries to sell certified emission reductions (CERs), or carbon credits, to industrialized countries. In other words, it allows a country with an emission-reduction or emission-limitation commitment under the Kyoto Protocol to implement an emission-reduction project in developing countries. Such projects can earn saleable CER credits, each equivalent to one ton of CO_2, which can be counted towards meeting Kyoto targets (Widowati, 2013; Condon and Sinha, 2013).

2 Problem definition and methodology

The main purpose of this paper is optimization of both stored CO_2 in reservoir and related ultimate oil recovery, simultaneously. To meet this goal, the following procedure should be done. To reduce the effect of allocated drainage area of each well on other ones, the reservoir constructed model is divided into sixty hypothetical zones. The next step is sensitivity analysis to distinguish the most effective parameters of reservoir model.

In the conventional genetic algorithm method, considering CO_2 storage and oil production, based on an expert's point of view economic function is defined (right part of procedure in Fig. 1). The best scenario will be obtained after implementation of single objective optimization.

In the second method as shown in the left part of procedure in Fig. 1, technical objective functions are defined without allocating weight for CO_2 storage and oil production functions. Then, by using a multi-objective non-sorted genetic algorithm (NSGA-II) a Pareto front diagram is generated. The Pareto front diagram depicts two optimized objects (technical objective functions). For both continuous gas injection and water alternating gas injection processes, after conducting multi-objective optimization, the best scenario is attained by then imposing the economic objective functions.

2.1 Sensitivity analysis

Sensitivity analysis is helpful to select proper input parameters in the optimization method. For this purpose, the D-Optimal Experimental Design is used. In this method, the optimized design matrix consists of n experiments. Maximization of $X'X$ determinant (X is model coefficient) and investigation of more areas in the experiment zone are performed in D-Optimal design (Triefenbach, 2008; Lawal, 2007).

2.2 Multi-objective optimization (MOOP) scenario

Many of the real world problems are generally characterized by the presence of many conflicting objectives. In the past, multi-objective optimization was considered as an application of single-objective optimization for handling multiple objectives. The single-criterion optimization problem has a single optimization solution with a single objective function. In recent years, several multi-objective evolutionary algorithms have been successfully applied to a wide variety of multi-objective optimization problems (Kurada et al, 2013; Brockhoff, 2013). It should be pointed out that there are some basic differences between the nature of multi-objective and single objective optimization methods. The general definition of a multi-objective optimization problem is as follows:

$$\begin{array}{lll} \text{Min/Max} & F_m(x) & m=1,2,\cdots,M \\ \text{Subject to} & g_j(x)\geq 0 & j=1,2,\cdots,J \\ & h_k(x)=0 & k=1,2,\cdots,K \\ & x_i^{(L)}\leq x_i\leq x_i^{(U)} & i=1,2,\cdots,n \end{array} \tag{1}$$

X is a vector of n decision variable.

$$X=\left(x_1,x_2,\cdots,x_n\right)^T \tag{2}$$

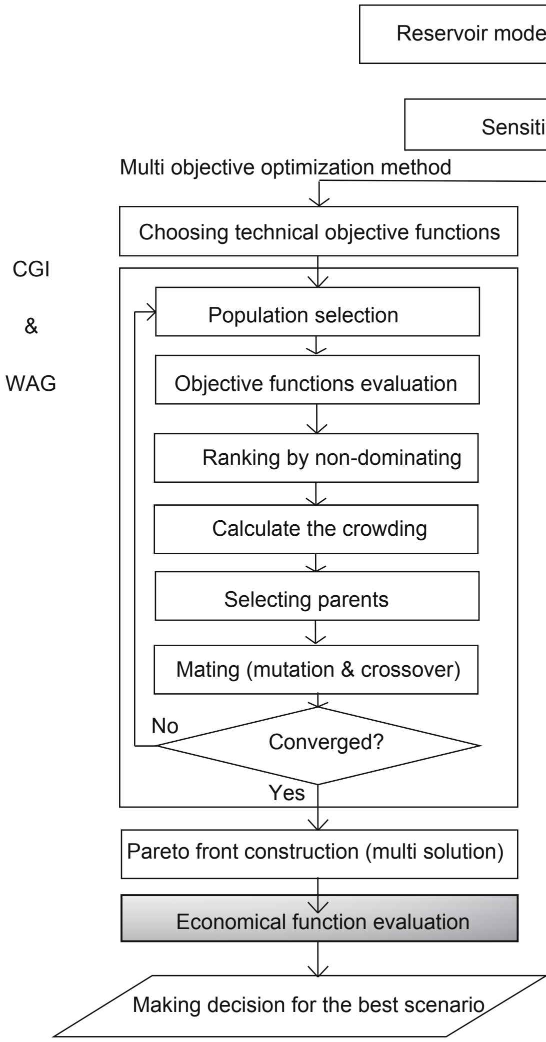

Fig. 1 Proposed algorithm for simultaneous optimization of CO_2 storage and oil production during continuous gas injection (CGI) and water alternating gas (WAG)

$g_j(x)$ and $h_k(x)$ define the domain of decision variables that confine them between upper and lower limits x_i^U and x_i^L, respectively. The related domain constitutes decision variables (D).

X is a non-feasible solution, if it does not satisfy J+K constraints. All feasible solutions are named Feasible Region or Search Space. In Eq. (1), there are M objective functions that each one should be maximized or minimized. The multi-objective optimization problem is divided into a single objective problem by classic methods that have been suggested over the last four decades. In this period various algorithms have been declared and researchers developed these algorithms based on diverse hypothesis. In weighted sum methods that are subsidiary of classic methods, a unified objective results from multiplying of each objective to each proposed weight. For instance, if the gas storage volume and oil recovery are presumed as two objective functions, optimization will be done by maximizing the sum of weighted functions in the classic method. Even though this idea is not complicated it brings with itself an intricate question, what quantities are appropriate for weights to be chosen? Obviously, there is no unique answer. Usually, weights would be appraised proportionate to their objectives in the problem. Also, it is difficult to find a weight vector to get Pareto solutions in a specified region of objective space. In most nonlinear MOOPs, using a uniformly distributed set of weight vectors does not lead to a uniformly distributed set of Pareto-optimal solutions. Since this mapping is not usually known, it becomes difficult to set the weight vectors to obtain a Pareto-optimal solution in a desired region in the objective space. Moreover, different weight vectors need not necessarily lead to different Pareto-optimal solutions (Marler and Arora, 2004; Xie et al, 2008).

2.3 Conventional definition of objective function

In the past, most objective functions in EOR studies were defined (with or without consideration of gas storage) as a single goal. The general form of these functions is as follows:

$$\begin{aligned}&\text{Objective function}\\&\quad=\left\{\text{Revenue/Cost (or) Oil production volume}\right\}_{\text{EOR process}}\times W_1+\\&\qquad\left\{\text{Revenue/Cost (or) Oil production volume}\right\}_{CO_2\ \text{storage process}}\times W_2\end{aligned} \tag{3}$$

where, W_1 is the enhanced oil recovery process weight factor; W_2 is the CO_2 storage process weight factor.

In most cases, the value of these weight factors is 0.5. For instance, Kovscek (2004) presented Eq. (4) as a combination of dimensionless recovery factor and dimensionless CO_2 stored in the reservoir.

$$\text{Objective function} = w_1 \times \frac{N_P^*}{\text{OIP}} + w_2 \times \frac{V_{CO_2}^R}{V^R} \tag{4}$$

where $w_1(0 \le w_1 \le 1)$ and $w_2 = 1 - w_2$ are weight factors, $V_{CO_2}^R$ is CO_2 stored in the reservoir, V^R is reservoir pore volume, OIP is the oil in place before CO_2 injection and N_P^* is the net oil production after CO_2 injection. Jahangiri et al (2010) introduced an objective function and similar to the previous studies (Kovscek, 2004; Ghomian, 2008), an equal weighting (w_1=w_2=0.5) was considered. The same format as Eq. (3) is provided in all the objective functions that cover economic parameters such as inflation, taxes and depreciation. In this study, a single objective function with a similar form to Eq. (3) is proposed in order to compare it with the multi-objective optimization.

$$NPV = \sum_{\text{Year}=1}^{\text{Year}=20} \left[(RE - CO) \times DF \right]$$

$$RE = RE_{\text{oil}} \times INR_{\text{oil}} + RE_{\text{gas}} \times INR_{\text{gas}} + RE_{\text{sequestration}}$$

$$CO = CO_{\text{oil}} \times INC_{\text{oil}} + CO_{\text{water}} + CO_{\text{reinjection}} \times INC_{\text{reinjection}} + CO_{\text{gas-injection}} \times INC_{\text{gas-injection}} + CO_{\text{water-injection}} \times INC_{\text{water-injection}} + CAPEX \tag{5}$$

where,

RE_{oil}: Income from oil sale

RE_{gas}: Income from gas sale

$RE_{\text{sequestration}}$: Income from CO_2 sequestration

CO_{oil}: Cost of oil separation

CO_{water}: Cost of water separation

$CO_{\text{reinjection}}$: Cost of re-injection of CO_2

$CO_{\text{gas-injection}}$: Cost of gas injection

DF: Devaluation factor

$CAPEX$: Capital expenditures

$INR_{\text{gas}}, INR_{\text{oil}}$: Oil and gas price inflation factor

$INC_{\text{water-injection}}, INC_{\text{gas-injection}}, INC_{\text{reinjection}}, INC_{\text{oil}}$: Inflation factor of all the costs

2.4 Non-dominated sorting genetic algorithm (NSGA-II)

NSGA II is an elitist non-dominated sorting genetic algorithm to solve multi-objective optimization problems. The computational complexity of NSGA II is also less than other multi-objective evolutionary algorithms. The steps involved in the NSGA II algorithm are described below:

Step 1: To initialize population. The initial population is generated using uniformly distributed random numbers.

Step 2: To determine all the objective functions values, separately.

Step 3: To rank the population using the constrained non-dominating criteria. The first non-dominating front is generally assigned a rank of one and so on. The answers having lesser rank are the better candidates to be selected for the next generation.

Step 4: To calculate the crowding distance of each solution.

Step 5: Selection is performed according to the crowding distance operator.

Step 6: Applying crossover and mutation operator to generate children solutions.

Step 7: The children and parent population are combined together in order to implement elitism and the non-dominating sorting is applied on the combined population.

In this paper, oil production volume and stored CO_2 volume in the reservoir are considered as objective functions in the multi-objective genetic algorithm optimization (Fig. 2).

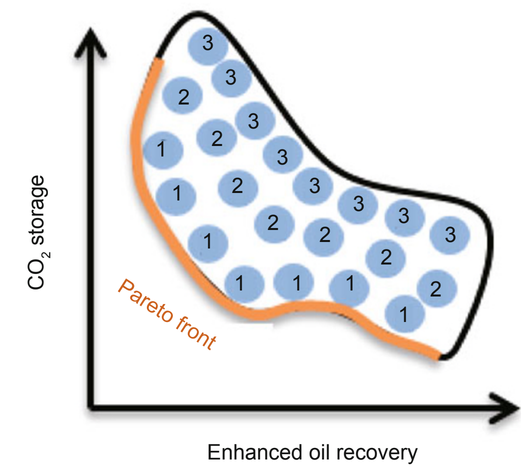

Fig. 2 The concept of non-dominating front (Pareto Front)

3 Model description

A model with four producers was used to implement different optimization methods. The saturations of different fluids are depicted in Fig. 3. The initial reservoir pressure is 3,332 Psia (undersaturated) and the average depth of the first layer is 8,026 ft. The average horizontal and vertical permeabilities are 252 and 6.5 md respectively. The reservoir model has 7,200 grid block and the average porosity is 16.25 %. Other properties are shown in Table 1.

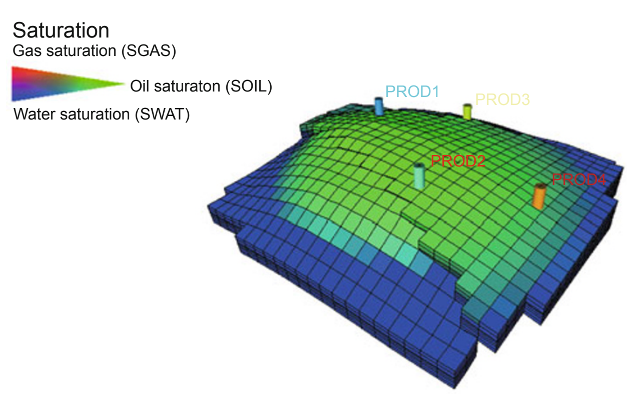

Fig. 3 Schematic of reservoir model and initial distribution of fluids saturation

Table 1 Some properties of the reservoir under study

Initial oil saturation	Dimension	Average block size in *Z* direction	Average block size in *Y* direction	Average block size in *X* direction	Pore volume
30%	25×24×12	436 ft	452 ft	44 ft	1.3×10^9 ft^3

In order to avoid well drainage area interferences and to decrease optimization time, a hypothetical zonation of the model is performed (Fig. 4). Injection wells can be drilled in the red spots (60 positions). Considering the number of injection wells, the optimizer prevents wells being drilled in the same position.

The values used to calculate the economic objective function are shown in Table 2.

Table 2 Economic parameters used in the optimization process

Parameter	Value, $	Parameter	Value, $
Income from the sale of oil [per barrel]	80	Separation and reinjection of CO_2 [per MSCF]	25
Income from sale of gas [per MSCF]	4	CO_2 injection cost [per MSCF]	5
Revenue caused by the storage of CO_2 [per ton]	8	Water injection cost [per barrel]	5
Rate of devaluation	0.12	Drilling cost [per well]	5,000,000
Oil separation cost [per barrel]	2	Oil and gas inflation rate	0.10
Water separation cost [per barrel]	5	Cost inflation rate	0.05

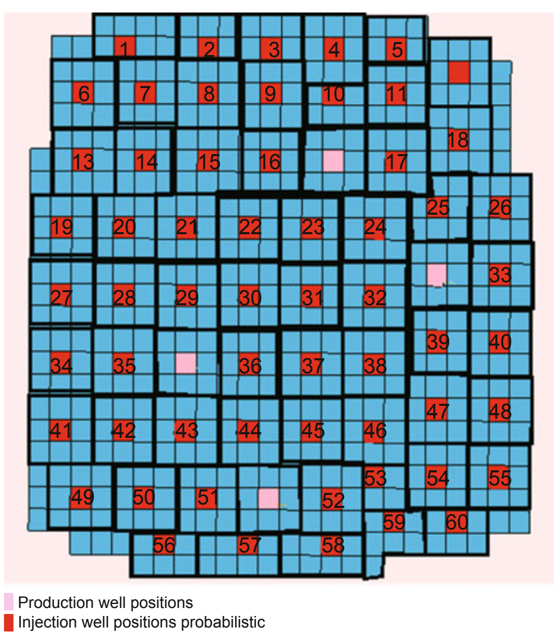

Fig. 4 Possible position of injection wells (after determination of first well location, this position is removed automatically and the location of the second well has to be in another place)

4 Results

The proposed workflow is applied to a reservoir model. After implementation of sensitivity analysis, different optimization methods are employed for different injection methods.

4.1 Reservoir model sensitivity analysis using D-optimal method

Design Expert software is used to analyze different parameters (Table 3). The 375 experiments are designed and results are analyzed by automatic data transferring between Design Expert, Eclipse 300 and Matlab.

Table 3 Parameters used in model sensitivity analysis

Parameter	Lower limit	Upper limit
Number of injection wells (*Z*)	1	3
Location of injection wells (*A, B, C*)	1	60
Upper perforation of injection wells (*D, E, F*) and production wells (*K, L, M, N*) [Block]	1	7
Perforation length of injection wells (*G, H, J*) and production wells (*O, P, Q, R*) [Block]	3	5
CO_2 injection rates (*S, T, U*), MSCF/Day	3000	19000
Oil production rates (*V, W, X, Y*), STB/Day	1500	7000
The purity of injection CO_2 (*A'*), %	90	100

The reservoir has been producing for 10 years. The effect of various parameters on different functions in continuous CO_2 injection for the next 20 years is examined. Accordingly, the effective parameters of three objective functions are identified. Results are shown in Table 4.

Table 4 Determination of effective parameters on reservoir responses

Objective function	Optimization method	Positive parameter	Negative parameter
NPV	One objective	*A-W*	*Z-S-T*
Total oil production	Multi-objective	*M*	*B-V-A-S-Z-W*
Total stored CO_2	Multi-objective	*T-U-S-Z*	-

Location of injection wells and oil production rate have a positive impact on NPV, and the number of injection wells and injection rate of CO_2 have negative effect. Oil production volume increases with increasing perforation interval, while the increasing number of injection wells, oil production rates and CO_2 injection rates have a negative impact on oil production volume. As expected, location of injection wells also affects the amount of oil produced. The amount of CO_2 stored in the reservoir is sensitive to injection rates and the number of injection wells. As can be seen, the factors that have a positive impact on the amount of gas storage have a negative effect on the oil production.

Results of sensitivity analysis show that if the amounts of produced oil and stored CO_2 are considered as two separate objective functions, the model will be sensitive to the length and location of perforation. But, if NPV (combination of them) is considered as a response, the model is not sensitive to the location and length of perforation. In fact, defining a single objective function from a real multiple objective functions can eliminate some effective parameters. The characteristics of single-objective and multi-objective optimization methods are shown in Tables 5 and 6.

Table 5 Characteristics of single and multi-objective genetic algorithm optimization process used in a continuous injection of CO_2

Characteristic	Single objective	Multi-objective	
Injection type	Continuous	Continuous	Alternating
Generation	100	100	100
Population size	50	50	55
Number of parameters	25	25	29
Pareto factor	-	0.4	0.4
Crossover factor	0.8	0.8	0.8
Mutation factor	0.2	0.2	0.2
Tolerance	10^{-6}	10^{-4}	10^{-4}

Table 6 Parameters with their upper and lower limits in single and multi-objective genetic algorithms

Parameter (No. of variables)	Lower limit	Upper limit
Location of first injection well (1)	1	60
Location of second injection well (1)	1	59
Location of third injection well (1)	1	58
Upper perforation limit in injection wells (3)	1	7
Lower perforation limit in injection wells (3)	3	5
Upper perforation limit in production wells (4)	1	7
Lower perforation limit in production wells (4)	3	5
Gas injection rates (3)	3000	19000
Oil production rates (4)	1500	7000
Number of injection wells (1)	1	3
Water gas ratio (1)*	1	5
Water injection ratios (3)*	3000	19000

Notes: * For water alternating gas injection only, five case of water gas ratio (gas: water) are 1:1, 2:1, 1:2, 1:3, 3:1.

4.2 Optimization of continuous gas injection using a conventional genetic algorithm (single objective)

Required time for optimization of continuous gas injection using conventional genetic algorithm is 128 hours. Reservoir has produced naturally for 10 years. Injection scenarios will be started at the end of the tenth year and continue for 20 years. In this time, effective operating parameters should be optimized. Combination of objectives in the conventional genetic algorithm is required. To do this, economic parameters are commonly used. In the single objective optimization method, economic parameters must be introduced before the start of the optimization process. The process of single objective optimization is shown in Fig. 5.

Due to the average change in objective function being lower than 10^{-6} in the last generation, the optimization process ultimately stopped in generation 58 (*NPV*=\$2.65 billion). The optimum control parameters are shown in Fig. 7. The second and third injection wells are located roughly in the oil zone and the first injection well is located in the water zone.

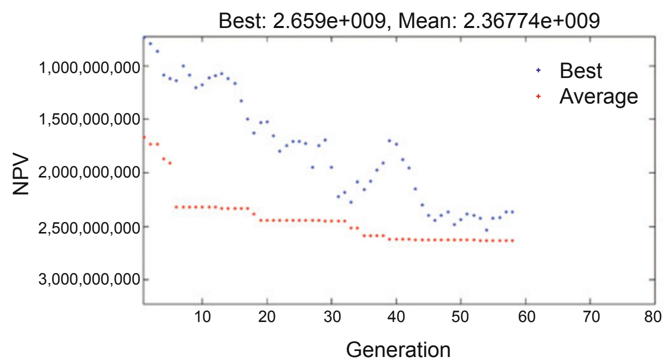

Fig. 5 Optimization of net present value using a conventional genetic algorithm (single objective)

4.3 Optimization of continuous gas injection using the multi-objective genetic algorithm

In order to use a non-dominated sorting genetic algorithm (multi-objective), two separate objective functions are defined:

Objective function 1: Total oil production

Objective function 2: Total stored CO_2 in-place

These technical objective functions are selected independent of economics. So, it is not necessary to scale them to the NPV values. In this method, objectives are optimized independent of price fluctuation. In other words, objectives are optimized directly, rather than indirect optimization of objectives (scale up them to *NPV* value) in conventional method. The properties of the method are shown in Table 5.

Fig. 6 depicts seven optimized continuous gas injection scenarios. Also, the corresponding optimized scenario by using the conventional method is shown. The values of optimized parameters for three groups of multi-objective optimization are shown in Table 7. The optimized scenarios are divided into three groups. The first group consists of optimum solutions in which maximization of the amount of stored gas is considered. However, as far as possible the

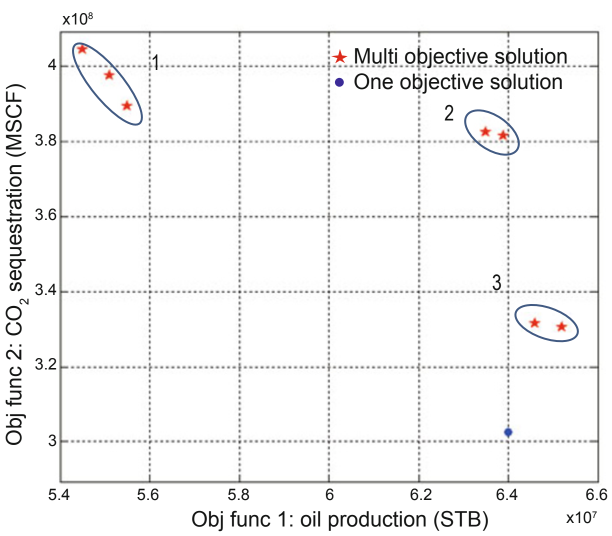

Fig. 6 Continues gas injection Pareto Front, resulting from the multi-objective genetic algorithm, and comparison with the single objective optimization

amount of produced oil is optimized. Optimized scenarios with maximizing of total oil production are considered in group 3. The second group is the most ideal situation, maximization of two objects is implemented regardless of the operating and financial restrictions. It should be noted that all of these scenarios are optimized from the multi-objective optimization point of view. The unique advantage of the mentioned approach is its decision-making for different economic and operational situations. The important point is the good result of the third group in comparison with that from the conventional method. The solution of single objective function optimization is located near to the third group.

Accordingly, in the third group, total oil production and total stored CO_2 in-place are increased by 1.2 Mbbl and 29 MMMSCF, respectively. These comparisons are done in the same condition where no operational and economic limitations exist. Because of direct optimization of total oil production and stored CO_2, various economic programs can be investigated and the best scenario among the existing solutions can be obtained. Achieving optimal solutions obtained from multi-objective optimization method using single-objective method would be practically impossible. First, the single-objective optimization must be performed several times for different weights, and is costly and time consuming in the actual field. For a specific reservoir, the time required to reach a Pareto optimal solution with the multi-objective method is 144 hours. To get these solutions (assuming that weight functions are determined) using single-objective optimization, the required time is about 900 hours. Second, weights which may lead to an optimal solution are unknown.

4.4 Optimization of water alternating gas injection using the multi-objective genetic algorithm

The water-alternating-gas (WAG) injection process due to its unique benefits in terms of enhanced oil recovery is helpful. Fig. 7 shows a comparison between the multi-objective optimization results of continuous and alternating injection.

Results show that WAG process is more efficient than CGI in enhancing oil recovery. While the amount of stored CO_2 in-place has declined significantly.

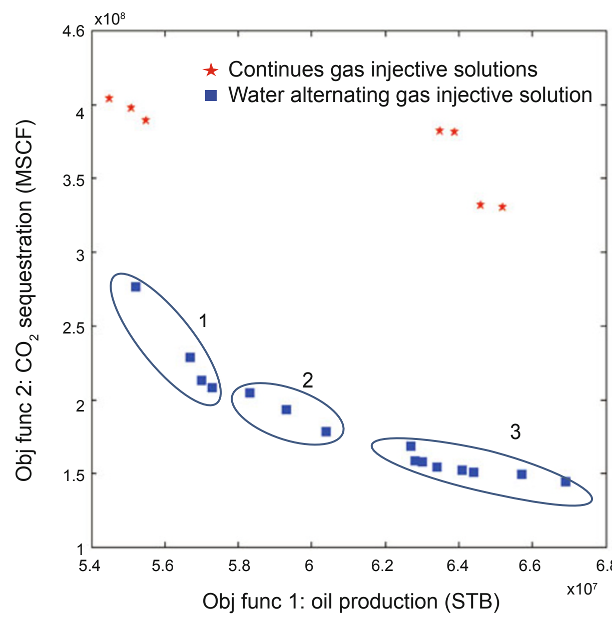

Fig. 7 Comparison the optimization results of continuous and alternating injection using the multi-objective genetic algorithm

Table 7 Optimized values of parameters for different injection methods

Optimization method (Injection type)	Group	Inj. wells positions			Upper perforation of inj. wells			Perforation length of inj. wells			Upper perforation of prod. wells				Perforation length of prod. wells				Gas injection rate × 1000 (MSCF)			Oil production rate × 500 (STB)				Water injection rate × 1000 (STB)			No. of injection wells	Gas water ratio
		Inj. Well 1	Inj. Well 2	Inj. Well 3	Inj. Well 1	Inj. Well 2	Inj. Well 3	Inj. Well 1	Inj. Well 2	Inj. Well 3	Prod. Well 1	Prod. Well 2	Prod. Well 3	Prod. Well 4	Prod. Well 1	Prod. Well 2	Prod. Well 3	Prod. Well 4	Inj. Well 1	Inj. Well 2	Inj. Well 3	Prod. Well 1	Prod. Well 2	Prod. Well 3	Prod. Well 4	Inj. Well 1	Inj. Well 2	Inj. Well 3		
One obj. (continuous)	-	48	52	39	1	2	7	4	5	3	6	3	7	3	5	3	5	4	13	17	12	14	14	10	9	-	-	-	3	-
Multi obj. (continuous)	1	55	53	40	7	7	4	5	5	4	6	4	3	6	4	4	4	4	19	18	18	12	14	14	10	-	-	-	3	-
	2	48	54	33	7	3	3	4	4	4	6	3	2	5	5	4	4	4	17	18	18	12	14	13	7	-	-	-	3	-
	3	33	46	26	6	6	3	5	5	4	4	6	5	5	4	4	4	4	15	17	14	13	14	11	7	-	-	-	3	-
Multi obj. (alternating)	1	48	33	51	4	4	6	4	4	4	5	4	4	6	4	4	5	4	17	18	16	12	13	9	12	11	8	18	3	5
	2	14	31	52	3	4	5	5	4	4	6	4	5	5	4	4	4	4	11	15	11	13	13	11	10	10	9	14	3	2
	3	14	31	58	2	4	5	5	4	4	6	4	6	6	3	5	4	4	10	9	11	14	13	11	11	10	15	14	3	2

4.5 Evaluation of scenarios in different economic situations

Applying economic parameters after implementation of optimization is a unique feature of the non-dominated sorting genetic algorithm. Entering these parameters before the optimization process in single-objective optimization may lead to improper results, if economic parameters change. Table 8 lists the results of both single and multi-objective optimization methods. One of the key economic parameters for selection of the optimum solution is the tax on CO_2 emissions. If emission tax is not considered, the third group of optimum solutions in continuous gas injection is suitable and provides more benefit than the conventional method. In this group the optimizer proceeds to achieve more oil production. Due to zero emission tax, CO_2 storage is less important.

Table 8 Comparison of net present value for different CO_2 emission taxes

No.	Injection type	Optimization method	Time of implementation hr	Group number	Oil recovery %	Stored CO_2 in-place MMMSCF	NPV with no tax \$ billion	NPV with 300\$ per ton tax \$ billion	NPV with 600\$ per ton tax \$ billion
1	Continuous	One objective	128	-	16.0	302	2.65	7.27	11.9
2	Continuous	Multi-objective	144	1	13.7	404	1.83	8.01	14.2
				2	15.9	382	2.46	8.30	14.1
				3	16.3	330	2.71	7.76	12.8
3	Alternating	Multi-objective	150	1	13.8	276	3.06	7.28	11.5
				2	14.9	193	2.61	5.57	8.5
				3	16.8	144	2.02	4.22	6.4

Considering a tax of \$300 per ton of CO_2, the answer is not appropriate anymore. In this case both objectives are important and the second group has more benefit of \$1.03 billion in comparison with the conventional method. In the last scenario, an emission tax of 600\$ per ton of CO_2 is considered. The first group with a higher level of benefit of \$2.29 billion than the conventional method is chosen. As can be seen, the WAG process does not have much benefit in terms of CO_2 storage in any amount of tax. Because of the injection of water, the storage volume for CO_2 decreases and the amount of oil production increases. Using the WAG process is appropriate when oil prices are high or the tax on CO_2 emissions is not considered.

5 Conclusions

This study set out to determine the application of a multi-objective genetic algorithm to strengthen decision-making in various contexts due to volatility of prices and CO_2 tax. Proposed and conventional methods were applied to an oil reservoir. The following conclusions can be drawn from the present study:

1) Using multi-objective optimization increases our decision-making power in different economic conditions including volatility in oil prices and CO_2 emissions tax. This leads to reduced risks and time for making new decision based on upcoming situations.

2) Time of optimization in the multi-objective optimization method will be shorter in comparison with single-objective optimization and therefore faster decision-making is provided.

3) From the viewpoint of petroleum reservoir managers, sequestration of CO_2 is more attractive in comparison with EOR in case of increasing CO_2 emissions tax.

4) In the proposed case study, oil recovery factor has increased significantly using CO_2 gas injection in addition to satisfying the environmental concerns of CO_2 emission.

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