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A synergy between the genetic algorithm and simulated annealing in a gas allocation optimization problem

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ABSTRACT

Usually, in gas lift operation there is a limited amount of lift gas that should be allocated between some wells in a way that the total produced oil maximized. For this purpose, different optimization algorithms (such as a genetic algorithm) are used. Generally, these algorithms have different internal parameters based on them; the resulted optimum point is affected. To find the best optimizer's parameters, it is usual to change one parameter and set other ones to a constant value, and again change another parameter and set others to a fixed value. This method needs the different runs of the optimizer (with different optimizer parameters) and it is clear that it is very time-consuming. Here is a new approach simulated annealing has coupled with a genetic algorithm. The genetic algorithm optimizes the gas allocation rates and simultaneously simulated annealing optimizes the genetic algorithm parameters. Results show that this new mean is much faster than the changing variable method, as well as the quality of its optimum point, which is much better than other methods (changing variable method).

1. Introduction

As oil production of a specific reservoir continues its pressure declines, and thereupon the production rate reduces. This pressure reduction continues until there is not economic to carry on oil production. In this situation, artificial lift methods such as gas lift are used. In the gas lift, gas is injected to a specific point from the annulus to tubing, here it solves in oil and reduces the oil column weight, thus the back pressure on the reservoir reduces and production oil rate will increase (Takács, 2005).

Usually, in actual cases, there is a limited amount of lift gas that should be allocated between some wells in a way that the total production is maximized. In fact, this is some kind of optimization problem that wants to find the best series of injection rates (of different wells) that maximizes the total produced oil and the total injection rates of wells should not exceed a specific value (the total amount of available lift gas). There are different algorithms for this optimization such as a genetic algorithm. Genetic algorithm is a heuristic way to find the best allocation, in the first step it assumes some solution (a series of numbers that each one stands for a well injection rate), algorithm evaluates the total production rate of each solution and selects the best ones, afterward the population of solutions is extended by mutation and crossover and again each solution is evaluated, in among them an individual with satisfying fitness function found, the algorithm is over otherwise again best individual is selected, their population are extended and algorithm is continued.

In genetic algorithm, there are different parameters which determine the speed of the algorithm and the quality of the optimum point, most important parameters are the initial population size, elite count (elite is the number of individuals that are selected to go directly to next iteration in the algorithm), the percent of the population that should be created by crossover (Pc) and the percent of the gens that are changing during the mutation (Pm). Many works are done to find the best set of parameters to have the most efficient optimization.

Aine et al. (2009) controlled evolutionary algorithm (EA) parameters based on a probabilistic profiling method. He considered a tradeoff time and a rigid time scale in his studies. Eiben and Smit (2011) discussed different methods for tuning the parameters of evolutionary algorithms and elaborate on how tuning can improve methodology. Leung et al. (2012) represented a method for controlling EA parameters which were called the Parameter Control system based on entire Search History (PCSH). He tested his method on GA and PSO algorithms. Fernández-Prieto et al. (2010) used the adaption strategy to tune the GA parameters then he used his model on testing the computer network under realistic traffic loads.

Liu et al. (2013) applied exploration and exploitation measures into adaptive parameter control. He used his method in solving chemical engineering problems. Yeguas et al. (2014) designed an automatic parameter tuning system that was based on Bayesian Networks and Case-Based Reasoning; his model was working well in static cases but not in dynamic ones.

Here is a new approach simulated annealing is used for optimizing the genetic algorithm parameters. Results show that this approach ends to an optimum point with great fitness function as well as it increases the speed of the optimizer.

2. Building the model

For testing the performance of the new method, first, six wells of Côte d'Ivoire oil fields are selected. Then the problem is to allocate a specific amount of lift gas in a way that the total oil production rate (sum of all wells production rates) is maximized. The amount of the available lift gas is limited and the problem has solved using the mapping method and previously introduced methods for dealing with constraints. One of the most important parts of the problem is defining the fitness function. In this study, this function should take the gas injection rates of all the wells as

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input and calculate the total oil production rate as output. Other properties of the reservoir and well are assumed to be fixed and their range is about the range of Côte d'Ivoire oil fields which are shown in Table 1. In the fitness function, first, the oil rate production of each well should be calculated. To calculate the oil rate of a well, nodal analysis is used. For this means, first, a fixed oil production rate is assumed, a wellhead is considered as the top node and the well is divided into about 200 ft sections in a way that the injection point and end of tubing are in the bound between two sections. Then an average pressure and temperature for the uppermost section are assumed and using the black oil correlations of Table 2, the fluid properties on the average pressure and temperature of the uppermost section are calculated. Afterward, using Ansari et al. (1990) correlation for two-phase flow and Hasan and Kabir's (1994) correlation for temperature estimation, the temperature and pressure at the bottom of that section are calculated. Then, using the new temperature and pressure, average pressure and temperature and fluid properties at the average pressure and temperature are calculated and using new properties the temperature and pressure at the bottom of the section are calculated. This procedure is repeated until the pressure at the bottom of the section is converged to a fixed value. The pressure of the bottom of the uppermost section is the top node pressure of the proceeding section and similar to the previous section, the bottom pressure of that is calculated. For applying the effect of lift gas, the lift gas is added to the gas phase of the fluid above the injection point. It is assumed that the lift gas was well mixed with the reservoir gas as it entered the tubing. Calculating the pressure at the bottom of the sections continued until the bottom hole pressure of the well was calculated. In this calculation, different correlations were used. These are the most accurate ones based on different literature (Brill and Beggs, 1974; Takács, 1989; Pourafshary, 2007; Bendakhlia and Aziz, 1989).

Table 1
Range of the parameter of each well.

	Maximum	Minimum
API	34.14	23.61
PI	2.75	1.64
P_R	4300	2900
WC	15	1.5
ID_t	4.87	2.75
D_{well}	10500	8300
P_{wh}	540	207
D_i	8500	3900
γ_{ginj}	0.92	0.68
ID_c	9.85	4.37
OD_t	5.33	3
IFT	64	50
γ_w	1.12	1.00
T_{wh}	180	110
γ_g	0.95	0.67
GLR	640	410
μ_o	3.54	1.97
T_R	315	200
P_b	650	430
Q_g	0.3	4
D_t	9,320	6,340
Orifice size	58	20

Table 2
Black oil correlations used in production modeling.

Properties	Correlations
Critical temperature and pressure	Standing
Dead oil viscosity	Beal
Gas compressibility factor	Papay
Gas viscosity	Lee
Inflow Performance	Vogel
live oil viscosity	Chew- Connally
Multiphase flow	Modified Hagedorn-Brown
Solution gas oil Ratio	Laster
Stability Criteria	Asheim
Surface Tension	Swerdloff
Temperature Profile	Hasan Kabir

After calculating the bottom hole pressure for a fixed rate, other production rates were assumed and their corresponding bottom hole pressure was calculated. Thus the production rate versus bottom hole pressure (TPR) was determined. And cross plotting was done with Vogel (1968) equation (IPR). The result was the calculation of the production rate of a well with a determined lift gas injection rate. Now, this procedure for other wells with their known gas injection rate is repeated and the oil rate production of each one is calculated. The production rates of all the wells are added and the Q_t (the sum of production rates as the output of fitness function) is calculated. In summary, here the fitness function input is the injection rate of all wells and its output is the sum of production rates of those wells.

Now it's time to optimize the gas allocation. We have some limited amount of lift gas and we want to allocate them between some wells. The problem is that the allocation should be in a way that maximizes the total oil production. Solving this problem is discussed in the next part.

3. Tuning the genetic algorithm parameters

Here as a new approach, simulated annealing is used to tune the genetic algorithm parameters. Simulated annealing can search the space and work well with just one individual, and in comparison with other algorithms is less sensitive to its parameters (like initial temperature and the function of temperature reduction). As well as in this algorithm the value of optimum point improvement can be standardized easily in different iterations (this standardizing would be discussed in preceding sections).

For that, the genetic algorithm has put inside the simulated annealing. First of all an initial population for genetic algorithm and initial values for genetic algorithm parameters as well as a temperature for simulated annealing supposed. Then the first iteration of the genetic algorithm ran and the value of total oil production improvement calculated; this improvement is the value of the fitness function of the simulated annealing. In each iteration of simulated annealing, if the value of its fitness was not improved, the algorithm uses the previous genetic algorithm parameters otherwise the new genetic algorithm parameters, which simulated annealing has created by modifying previous ones, are used. Fig. 1 shows a flowchart for this algorithm.

3.1. Fitness function for simulated annealing

In fact, the fitness function of the simulated annealing takes the parameters of the genetic algorithm and returns a value that shows the efficiency of the genetic algorithm. This value should show the improvement of the best individuals of the genetic algorithm not the best individual itself. Because it's probable that the parameters be in a way that the best individual does not improve but its value be a good value. Thus the value of the fitness function of the simulated annealing is considered as the improvement of the genetic fitness function. In a simple way, the simulated annealing (SA) fitness value should be considered as the difference of the genetic algorithm (GA) best point of the current iteration and the best point of the previous and next to the last iteration. But the problem of this method is that by continuing the algorithm the value of the GA fitness improvement decreases and this is not necessarily the result of the bad parameter selection, it's because as the algorithm approaches the optimum point naturally, the best point improvement decreases. Thus the fitness value of the SA should be standardized in some way. There are two ways to standardize the SA fitness function; one can consider the relative GA fitness improvement or the differences in improvement can be divided into temperature. Another parameter about the standardizing the SA fitness function is the population size, it's clear that when the population size is larger, the probability of finding a good individual is high, but the algorithm should calculate the fitness function for more individual and so its speed reduces, thus it is better to find the value of GA fitness improvement for one individual calculation or in other word divide the value of GA fitness function improvement to population size.

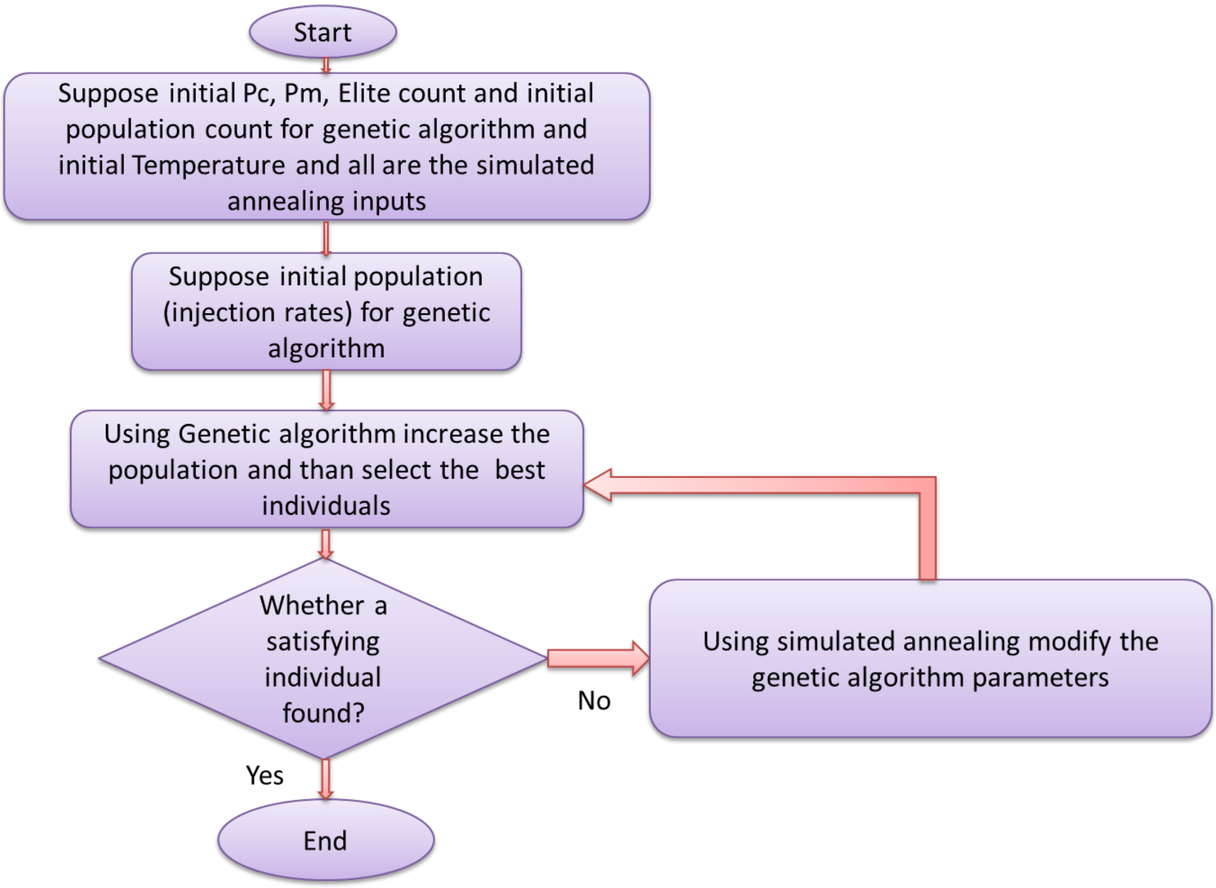

Fig. 1. Flowchart of genetic algorithm tuned by simulated annealing.

Here 10 wells of Côte d'Ivoire oil fields have considered and 6 MMscf of available lift gas should be allocated between them in a way that total produced oil maximized. In each case, the optimum point of gas allocated has calculated. Fig. 2 shows the convergence progress with different SA fitness function. Fig. 2 shows that the Tolerance/Population size/T has the best optimum point. And Tolerance has the worse approach, clearly, this Fig. 2 shows the effect of the standardizing the SA fitness function. Fig. 2 shows that as the standardizing has stiffened the value of optimum point has improved.

Now based on Fig. 2, we can select the Tolerance/Population size/T as the SA fitness function, the Tolerance is the difference of the last two iteration optimum values. Fig. 3 shows the value of the optimum points of the optimizer with different SA fitness function. As Fig. 3 shows again the Tolerance/Population size/T has led to the best optimum point, thus this SA fitness function would be selected as the best SA fitness function.

3.2. The method of changing parameters

One of the most common methods for setting the parameters is to set all parameter fixed and changing parameters. This method is used in different optimization problems in different thesis and different papers. Here this method would be compared with the method of this paper. As previously mentioned here genetic algorithm optimizes the lift gas injection rated and the simulated annealing optimizes the genetic algorithm parameters. The most important GA parameters are crossover probability, Pc (the fraction of the population of each iteration that is created by crossover), the mutation probability, Pm (the fraction of genes that are changing in a chromosome in mutation process), population size (of each iteration) and the elite count (the number of individuals that are directly going to next stage). Before we compare the method of this paper with the method of the changing variable, first we discuss the method of changing parameters.

As a standard state, we suppose a population size of 20, elite count of 3 and crossover and mutation probability of 0.8 and 0.05 respectively. Then each parameter would be changed (while other parameters are set to their standard value) and in each case, the value of optimum point has been calculated.

First, the value of population size is changing and with the different values, the amount of optimum point would be calculated. The change in optimum point value can be seen in Fig. 4. Fig. 4 shows that increasing the value of the population size until 20 has increased the value of total oil production (optimum point) but after that, the optimum point has not been improved. But increasing the value of population size increase the runtime of the program.

Another parameter is the value of the elite count. As Fig. 5 shows the elite count about 3 has the best performance and increasing or decreasing the value would decrease the optimum point. It is because when the value of the elite count is low, good individuals are not transferred to the next iteration and in a high value of elite count solution with low quality are transferred to next iteration and decrease the average quality of the individuals of each iteration.

Fig. 6 shows the effect of crossover probability on optimum point, as Fig. 6 shows the value of crossover probability has an optimum value and decreasing or increasing the Pc would decrease the optimum point value.

The last parameter is the mutation probability, Fig. 7 shows the effect of Pm on the optimum point, and this graph is similar to previous ones.

4. Results and discussions

As seen, the different parameters of the genetic algorithm changed and the optimum point of the genetic algorithm calculated. Now the best three-point of the above points (with highest total oil production) calculated and their values compared with the genetic algorithm that is coupled with simulated annealing of this paper. Fig. 8 shows the value of the optimum point of the method of this paper with those three best optimum points with the method of changing variables. As can be seen, the method of this paper has an optimum point with a much better value than other methods.

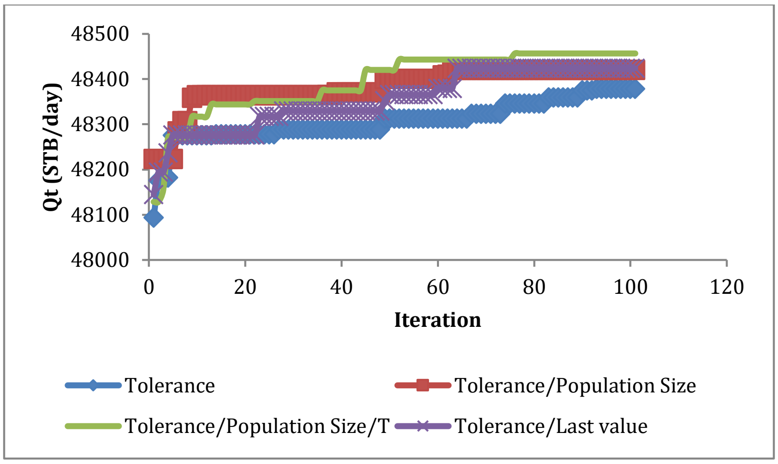

Fig. 2. Optimizer convergence with different SA fitness function.

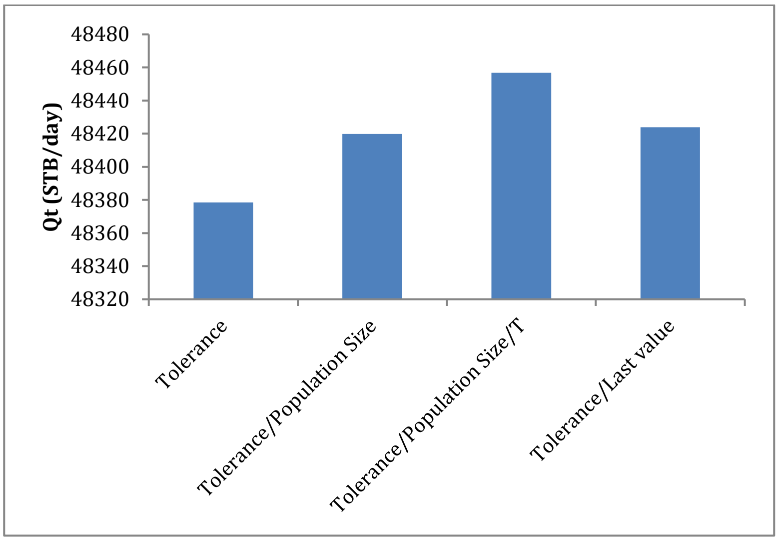

Fig. 3. The optimum point of the optimizer with different SA fitness function.

An optimizer is good if it had a good optimum point and can find it in minimum time. The standard method that is used to find the run time of the algorithm is to find the total amount of GA fitness function evaluation. Fig. 9 shows the total amount of GA fitness function evaluation of the referred best three methods and the method of this paper, as Fig. 9 shows, the required number of GA fitness function evaluation for finding the optimum point, in the method of this paper is much less in comparison with the other three method, thus the method of this paper is much faster than the method of changing parameters.

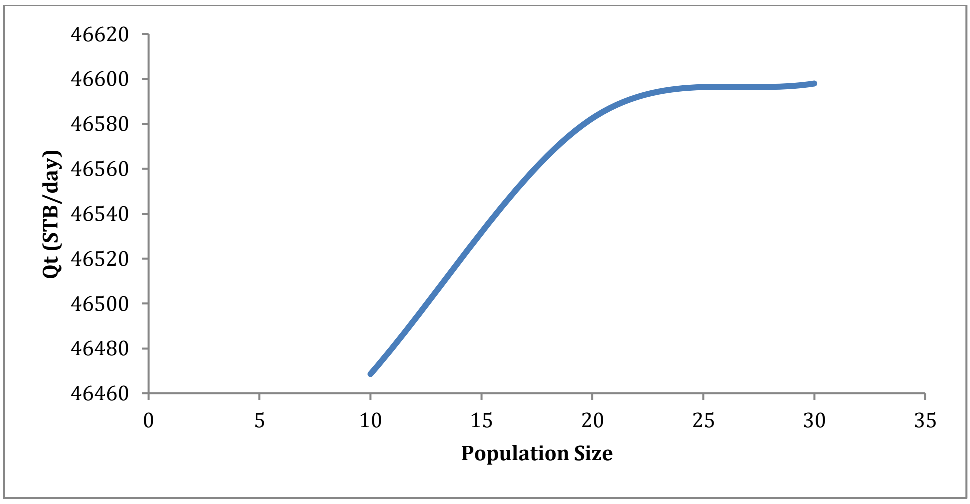

Fig. 4. The value of the optimum point with different amounts of the population size.

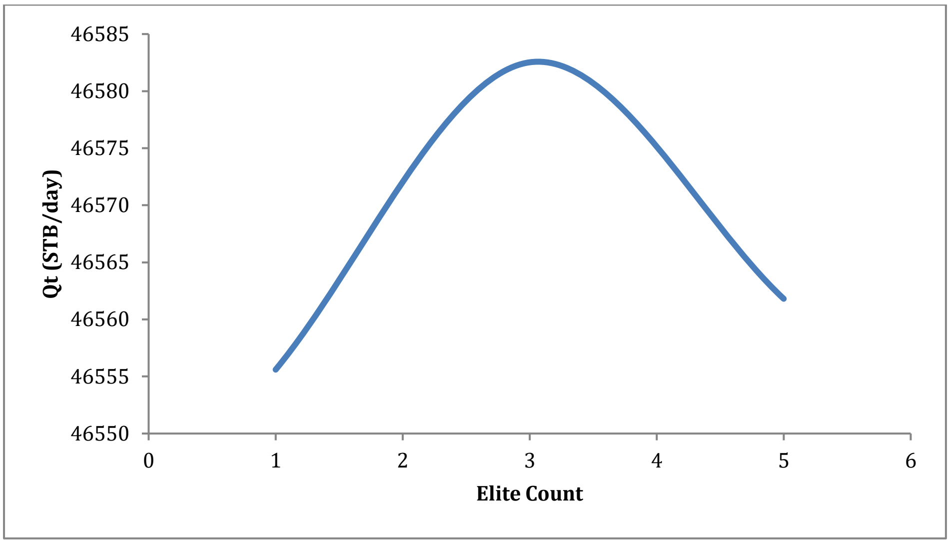

Fig. 5. The value of the optimum point with different amounts of elite count.

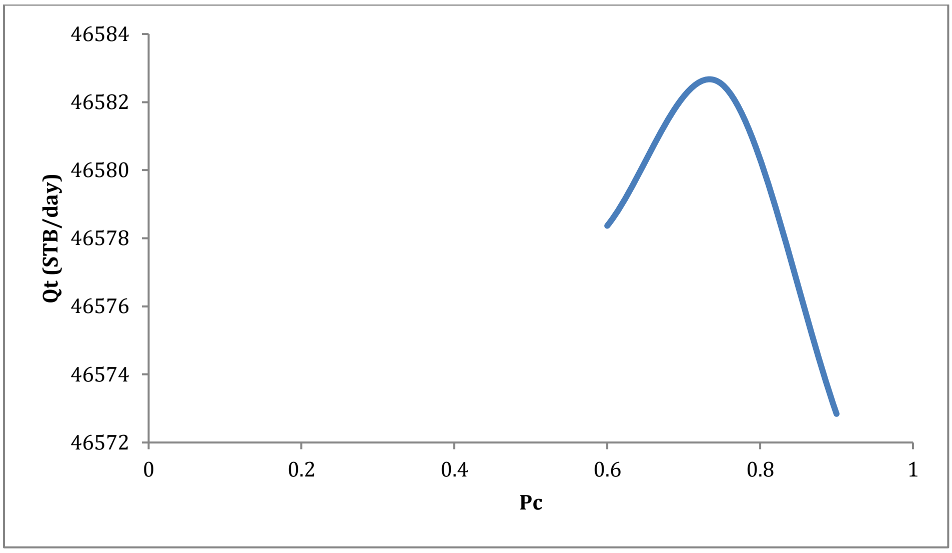

Fig. 6. The value of the optimum point with different Pc (crossover probability).

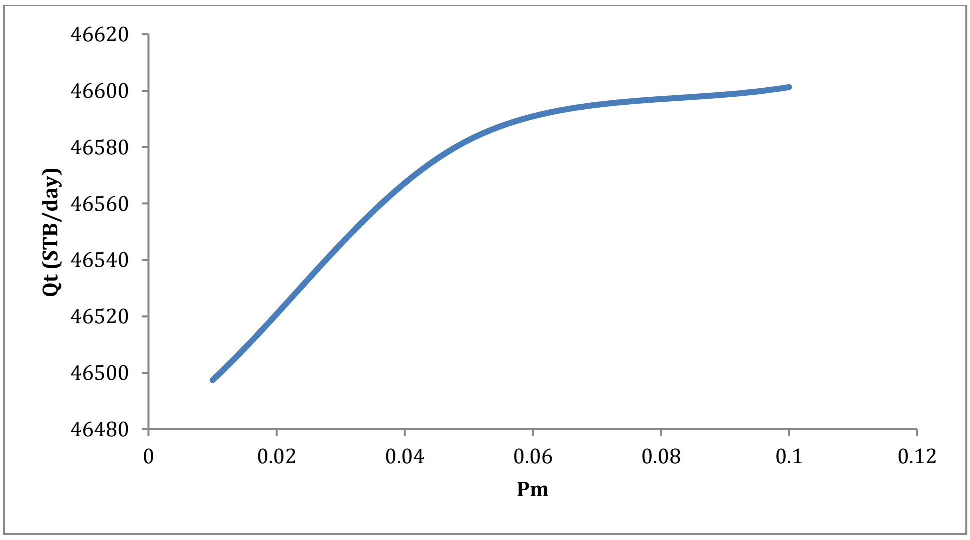

Fig. 7. The value of optimum point with different Pm (mutation probability).

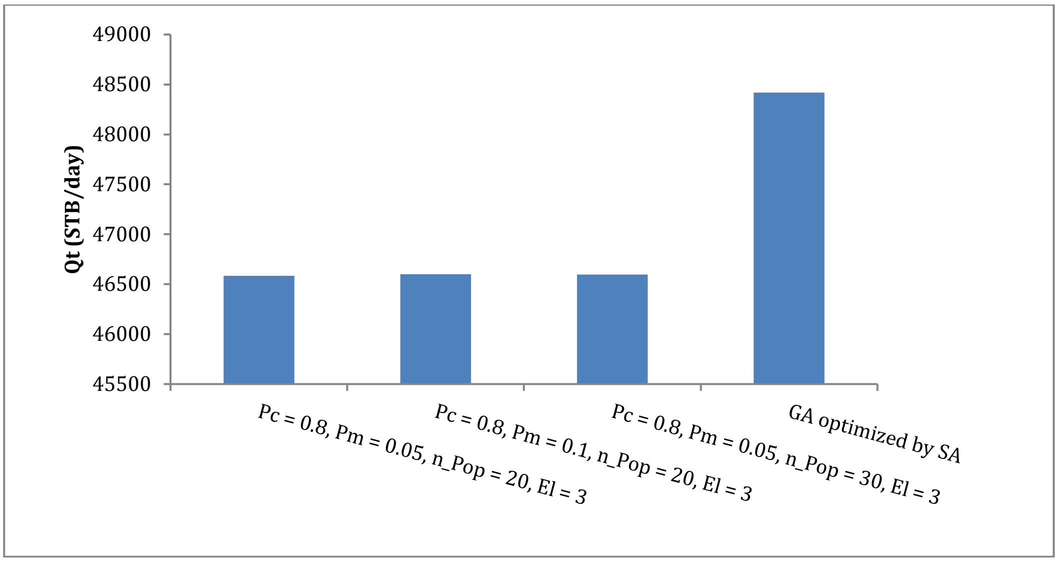

Fig. 8. Comparison of the three best values of the changing parameter method and the method of this paper.

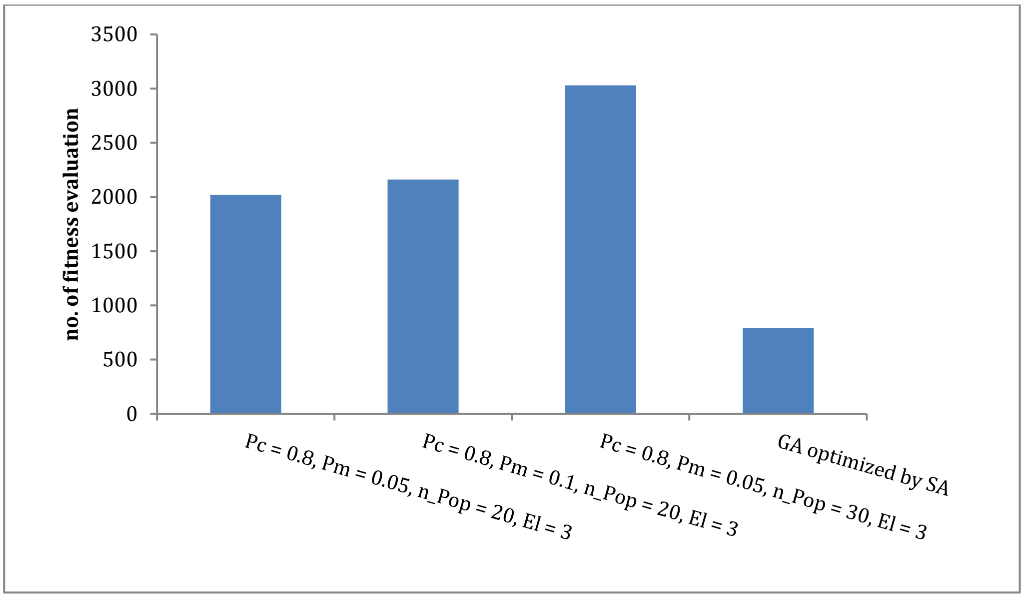

Fig. 9. The comparison of the required fitness function evaluation of the genetic algorithm with different parameters and the method of this paper.

5. Conclusion

1. The method of this paper uses the simulated annealing coupled with the genetic algorithm to optimize the genetic algorithm parameters. This method changes the genetic algorithm parameters during the optimization and finds good parameters for each iteration.
2. The method of this paper's optimum point is much better than the method of changing variables and leads to injection rates that led to a point with higher total oil production.
3. The speed of the new method is much higher than the method of changing variables.
4. In the usual genetic algorithm method it's needed to run the optimizer with different GA parameters and at last, select the best optimum point, but in the method of this paper, there is a need to run the optimizer just for one time and found the best optimum point.

List of symbols

API	*Oil Gravity, API*
D_i	*Injection depth, ft*
D_t	*Tubing depth, ft*
D_{well}	*Well depth, ft*
GLR	*Gas Liquid ratio, SCF/STB*
ID_c	*Casing inner diameter, in*
ID_t	*Tubing inner diameter, in*
IFT	*surface tension, dyne/cm*
OD_t	*Tubing outer diameter, in*
Orifice size	*Orifice size, 1/64 in*
P_b	*Bubble point pressure, psi*
PI	*Productivity index, STB/day/psi*
P_R	*Reservoir pressure, psi*
P_{wh}	*Well head pressure, psi*
Qg	*Injection gas, MMSCF/day*
Qt	*Total produced oil, STB/day*
T_R	*Reservoir temperature, F*
T_{wh}	*Well head temperature*
WC	*Water cut, %*
γ_g	*Gas gravity*
γ_{ginj}	*Injection gas gravity*
γ_w	*Water gravity*
μ_o	*Oil viscosity, cp*

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