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Development of an efficient hybrid GA-PSO approach applicable for well placement optimization

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Abstract:
When it comes to the economic efficiency of oil and gas field development, finding the optimum well locations that augment an economical cost function like net present value is of paramount importance. Well location optimization has long been a challenging problem due to the heterogeneous nature of hydrocarbon reservoirs, economic criteria, and technical uncertainties. These complexities lead to an enormous number of possible solutions that must be evaluated using an evaluation function (e.g., a simulator). This makes it necessary to develop a powerful optimization algorithm into which a fast function evaluation tool is incorporated. The present study describes the application of a combination of the genetic algorithm (GA) and the particle swarm optimization (PSO) into a hybrid GA-PSO algorithm that is implemented in a streamline simulator to determine optimal locations for production and injection wells across heterogeneous reservoir models. Performance of the hybrid GA-PSO algorithm is then compared to that of the PSO and the GA separately. The results confirm that compared to conventional methods, the recommended method provides a fast and well-defined approach for production optimization complications.

1. Introduction

Nowadays, the optimization and analytic technologies are of vital importance in enabling the oil and gas industry to achieve their maximum efficiency (Furman et al., 2017). The optimal production strategy is a fundamental step in integrated reservoir management, which widely influences on the productivity of a reservoir. One of the most important and at the same time, the most challenging problem along the optimization process is optimizing the well placement. There are essential concerns in the planning of many oil and gas field developments such as implementing efficient solutions to time-consuming problems, which facilities and improved recovery plans while contributing various limitations including: the priority of activities, quality standards, financial supply availability, risky path logic, fund limits (Wood, 2018). So, optimization of the well placement in a reservoir is a crucial reason for better sweep efficiency and high production rates.

Several challenges arise while determining the optimum well placement of production/injection wells due to the presence of multiple decision variables and the nonlinear nature of the problem (Al Dossary and Nasrabadi, 2016). Decisions were made concerning both the network structure and the operation profile while considering not only physical restrictions but also economic considerations (Lin and Floudas, 2003). Several requirements are needed before applying reservoir simulations and computational algorithms, which were regularly used in well placement studies, and these requirements will increase as the number of wells increases. It is, therefore, necessary to have an advanced optimization workflow for specified problems to find appropriate locations for wells in the reservoir by applying minimum iterations of numerical simulations. Many optimization approaches have been proposed for well control problems. Since this method is a multi-dimensional and multimodal challenge that usually carries different local optima, gradient-free algorithms have been used to solve these problems. To investigate the global optimum, although the gradient-free methods use the objective function values which were defined by implementing function assessments and do not need the determination of cost function derivatives, the gradient-base methods need them. Gradient-free techniques, which are appropriate for applying

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in production optimization, were assorted into two classes. The first class compromises deterministic techniques including: Hooke-Jeeves direct search, generalized pattern search, and mesh adaptive direct search method. The second one includes stochastic or global methods, i.e., genetic algorithm (GA), simulated annealing, particle swarm optimization (PSO), harmony search algorithm, imperialist competitive algorithm and covariance matrix adaptation evolution strategy (CAMES). The methods in the first group are very robust, which explore locally and require fewer function evaluations. However, they are susceptible to initial estimations of variables and can get trapped in local optima. In theory, methods of the second category overcome these problems but still have challenges including, no increase in objective function at each iteration and compelling several numerical reservoir simulations (Zandvliet et al., 2008).

In this study, the GA was combined with PSO to have a better estimation of locations for a set of vertical wells. Attempts were made to take the advantages (global search capability and accuracy of GA with local search ability and efficiency of PSO) of both algorithms into a single hybrid algorithm to achieve superior efficiency in the optimization of production planning.

The rest of this paper is structured as follows: Section 2 presents the related works. Section 3 outlines constituents that were used for optimizing the well placement: 1) GA, 2) PSO, 3) hybrid algorithm, 4) streamline simulation, and 5) objective function definition. Section 4 presents the optimization results and the efficiency of hybrid approach is compared to that of the PSO and the GA distinctly. Finally, the conclusions outlined from this study are represented in section 5.

2. Related work

GA seems to be the most common global optimization algorithm which used for optimizing the well placement and other related reservoir applications. Montes et al. (2001) optimized the location of vertical wells applying a standard GA. They studied two synthetic models and showed that the best mutation rate should be adjustable with generation. Bangerth et al. (2006) compared GA performance with other optimization approaches for well placement problems. They showed that the relative performance of the different methods is problem specific. Emeric et al. (2009) performed an integrated study based on GA to optimize the number, location, and trajectory of different deviated production and injection wells with nonlinear constraints. Morales et al. (2010) introduced modified GA for optimizing the location of horizontal wells in gas condensate reservoirs considering different parameters. They proposed a modification which allows user-defined level of risk to be integrated into the optimization scheme to find the optimum well locations. Onwunalu and Durlofsky (2011) defined PSO as a substitute for GA in several types of well placement optimization problems. They showed that PSO provides better results than those that employ GA for optimization problems. Beckner and Song (1995) employed the SA algorithm to maximize net present value by optimizing the schedule and location of horizontal wells by expressing the optimization as a traveling salesman problem. CMAES was used to optimize unconventional well locations in synthetic reservoir models (Ding, 2008). The CMAES algorithm was found to provide similar results to those gained by a continuous GA. Afshari et al. (2011) employed an improved harmony search algorithm to determine the best place for injection and production wells through conducting several case studies, including both synthetic and real reservoirs. They found that the improved harmony search algorithm provides comparable or better results than other stochastic algorithms such as GA and simulated annealing. Bellout et al. (2012) applied different local search optimization methods in a nested optimization approach for placement of joint wells and controlling well problems. Dossary and Nasrabadi (2016) determined the optimum locations for vertical and horizontal wells in an artificial reservoir using imperialist competitive algorithm. They outlined that imperialist competitive algorithm shows better results than other optimization algorithms studied in their research.

Hybrid methodologies require the combined use of two or more optimization algorithms. In this methodology, the methods are compensating each other's weaknesses, so the output is a well-defined method. Bittencourt and Horne (1997) applied a hybrid algorithm linking a polytope method to GA for determining the best placement of vertical or horizontal wells in a two dimensional reservoir. This hybrid approach was applied suitable to obtain the optimal solution efficiently. Guyaguler et al. (2002) utilized a hybrid optimization algorithm, which develops the local search ability of GA. They also used kriging and artificial neural networks as surrogates for costly reservoir simulations to accelerate the optimization procedure. Yeten et al. (2003) implemented a hybrid procedure by combining GA and a hill climber algorithm to optimize the unconventional well configurations. To perform an optimization process with the minimum function evaluation, they used near well upscaling and a proxy. Ciaurri et al. (2011) hybridized GA with deterministic methods to optimize well production rates in different case studies. They found this approach a more appropriate optimization technique than other common methods used for optimization. Ding et al. (2014) suggested a combination of a modified PSO and quality map to better determine the placement of wells. They showed that initializing the population using a quality map generally improves the efficiency of the optimization process. Aliyev and Durlofsky (2011) developed a hybrid algorithm by combining PSO and Hooke-Jeeves direct search to modify well locations in a reservoir. In their approach, PSO performed several iterations, and then the best PSO was selected and used as the initial point in Hooke-Jeeves direct search. They also demonstrated that the hybrid method provides better results than the PSO and Hooke-Jeeves direct search algorithms. Nwankwor et al. (2012) developed the differential evolution (DE) with PSO to optimize well patterns in a water flooding process and showed that hybrid optimization technique could considerably reduce the computational expenses. Isebor et al. (2013) employed a hybrid algorithm that is a combination of PSO and mesh adaptive direct search (MADS) as a local pattern search method, and verified that the hybrid technique is more reliable than PSO and MADS algorithms. Aliyev and Durlofsky (2017), presented a multilevel optimization procedure. They used the PSO-MADS hybrid algorithm for well placement and well control optimization over a sequence of up-scaled models.

3. Theory and methods

3.1 Genetic algorithm

The GA is a stochastic computation technique, which benefits a set of candidate solutions in all iterations, and is based upon the principles of natural evolution and selection (Goldberg, 1989). An individual is the name of each of these solutions, and a group of individuals forms the population. The initial population, which is generated randomly, is the aim of GA to evaluate the feasibility of each individual regarding its objective function. After that, the selection operator picks individuals with the highest value of cost functions within the population as parents to create new population. The selection selects the best individuals to be parents, and the cross over operator combined parents arbitrarily to produce new collections of individuals. During the generation of genetic chromosomes, the mating process occurs, which is analogous to biological mutation (Yazdanpanah and Hashemi, 2012). In mutation, a particular part of an individual would be adapted to a new value. Mutation in GA aims to prevent the algorithms from getting stuck in local optima and introducing diversity (Hassan et al., 2005). The computations are terminated when the stopping criteria is satisfied. It has been proved in several studies that the crossover and mutation probabilities are two parameters which have the most effect on the results of computations (Montes et al., 2001; Guyaguler et al., 2002; Yeten et al., 2003).

3.2 Particle swarm optimization

The PSO is a stochastic global optimization method developed by Kennedy and Eberhardt (1995). This method is based on the behavior of a colony or swarm of insects, a school of fish or a flock of birds. PSO uses a set of potential solutions in every iteration, which called particles, and the collection of these particles is named a swarm. A vector in a multidimensional search space demonstrates a particle within the swarm. This vector has a proprietary vector called the velocity vector that controls the next position of the particle. Conventionally, PSO starts its search from the initial swarm of particles which initialized with a random position and exploration velocity. The particles give the right positions to each other and adjust their positions and velocities according to the information obtained from the proper positions (Salman et al., 2002). The position of each particle is updated based on its objective function and position comparative to its former best position and the global best (Onwunalu and Durlofsky, 2011).

The position at iteration $m+1$ for particle i, denoted here as $P_i(m+1)$, is determined as follows:

$$P_i\ (m+1) = P_i\ (m) + V_i\ (m+1) \tag{1}$$

Velocity of particle i at iteration $m+1$, designated $V_i(m+1)$, is updated by the following equation:

$$V_i\ (m+1) = \omega V_i\ (m) + c_1 D_1 (m) .V_i^c (m) + c_2 D_2 (m) .V_i^s (m) \tag{2}$$

where $D_1(m)$ and $D_2(m)$ are diagonal matrices which, variables between [0, 1] are attributed to their elements, randomly, ω is inertia weight, c_1 and c_2 are acceleration constants with positive values (we use the PSO parameters approved by Clerc (1999), the quantities $V_i^c(m)$ and $V_i^s(m)$ are the cognitive and social components of velocity respectively, defined as:

$$V_i^c (m) = P_i^{best} (m) - P_i (m) \tag{3}$$

$$V_i^s (m) = P_i^{nbest} (m) - P_i (m) \tag{4}$$

where $P_i^{best}(m)$ is the best position found by particle i up to iteration m and $P_i^{nbest}(m)$ is the position of the best particle in the neighborhood of particle i. As shown in Eq. (2), the velocity equation consists of three parts, referred to as the physical, cognitive and social elements. The physical part $(\omega v_i(m))$ causes the particle to remain in its current path. The cognitive part (containing c_1) represents the particle experience about its previous best position and implements a velocity term in this manner. The social component (containing c_2) receives information about the best positions of any particle surrounding the particle i and leads to movement towards this particle. Hence, each particle flies to a new position according to its current direction, its own knowledge, and the cooperative experience of other particles. The PSO algorithm stops when total number of objective function evaluations were carried out.

3.3 Hybrid methodology

Although GAs have been successfully implemented to many reservoir optimization problems, using GAs for exploring multiple non-smooth search spaces with various local optima could be very expensive and time-consuming regarding the requirement of large number of reservoir simulations for convergence to an actual optimal solution. On the other side, PSO is able to reach the convergence in the early stage of the optimization process but may get trap in local optimum solution. Regarding the efficiency (high speed) of PSO and the accuracy of GA, linking the searching abilities of both methods seems to be an efficient approach (Juang, 2004). In this approach, we combine the global information obtained via GA into the local search abilities of PSO algorithm thereby keeping a reasonable balance between the social interactions and exploitation parameters of the algorithms.

As shown in Fig. 1, when solving an n-dimensional optimization problem, the algorithm starts from the first step with the generation of the initial individuals that are randomly crea-

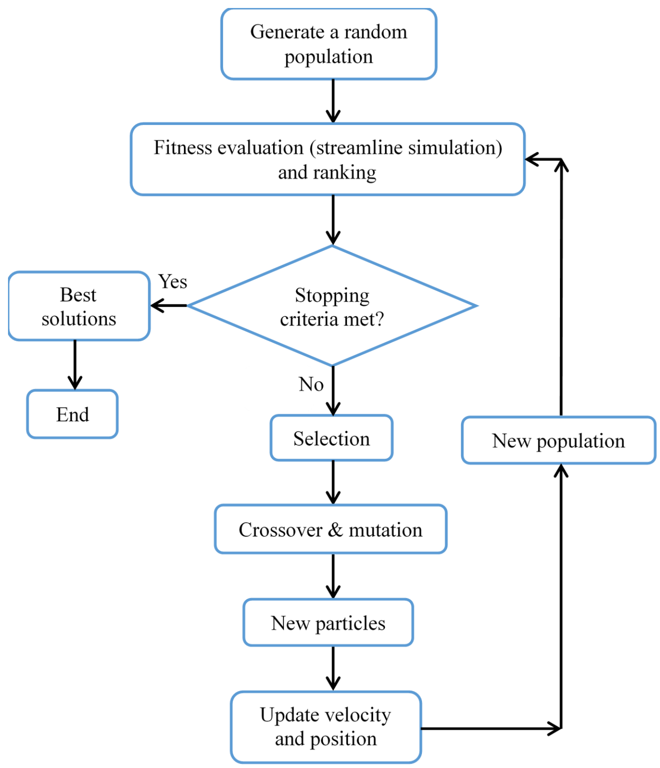

Fig. 1. Flowchart of HGAPSO.

ted. The fitness of each individual, in the evaluation step, is assessed through obtaining its objective function by the streamline simulator. The individuals are sorted by fitness, and the best solution vectors are supplied into the GA to generate new individuals by recombination operators. Then, the crossover operator is implemented by combining the strengths of two parents to update the best individuals with a crossover probability by the following equation (Radcliff, 1991):

$$I_i^{new} = \beta \cdot I_i^M + (1-\beta) \cdot I_i^F \tag{5}$$

where I_i^{new} is the i^{th} variable in a new individual, I_i^M and I_i^F are the property values of the same variable from the mother and father individuals, respectively, and β is a blending coefficient between zero and one that can remain constant for each crossover operation, or can be randomly selected for every single property (Abukhamsin, 2009). The mutation operator is another principal GA operator, which in that, a specific element of a solution vector or an individual is converted to a new state in accordance with the mutation rate by following equation (Haupt and Haupt, 2004):

$$I_i^{new} = I_i^{old} + \sigma \times \mathrm{N} \quad (0, \quad 1) \tag{6}$$

where I_i^{old} and I_i^{new} are the property values before and after mutation, respectively. N is a randomly appropriated number ranges from 0 to 1, and σ is the variance of this property. The new individuals generated from GA are used to the initial particles in the PSO technique. Then, velocity and position of particles are updated by Eqs. (1) and (2). The objective function of the newly created solutions is evaluated and sorted for repeating the entire run. The algorithm terminates as the maximum number of iterations is performed. The parameters used in the implementation of standalone algorithms are listed in Table 1. The same parameters used for the hybrid method.

Table 1. GA and PSO parameters.

GA	Value	PSO	Value
Mutation rate	0.2	Inertia weight	0.7298
Crossover rate	0.8	Acceleration constants	1.4962
Selection fraction	1	Swarm size	8-12
Population size	8-12		

3.4 Streamline simulation

Reservoir simulation has become the standard practice to solve challenges in the oil industry. Due to the nonlinearity and complexity of the optimal well location problems, the optimization process may involve many reservoir simulation runs and the optimization process will be extremely time-consuming and expensive. There are several techniques presented in the previous literature for numerical simulation of oil and gas reservoirs. Both finite element and finite difference discretization of the continuity equation can be used. The main disadvantage of these techniques is that simulation run time will increase exponentially with a linear progression in the search space (Afshari et al., 2011).

This study proposed streamline simulation to achieve more efficient and robust optimization procedure, especially for simultaneous placement of several wells. The advantages of streamline simulation methods over the traditional methods include: better computational effectiveness, less numerical dispersion and minimization of grid orientation effects (Samier et al., 2001).

The main equation in terms of pressure (p), for incompressible and multiphase flow in permeable media is given by (Batycky et al., 1996):

$$\nabla \cdot K \cdot (\lambda_t \nabla p + \lambda_g \nabla D) = 0 \tag{7}$$

where D represents a depth below the datum point in ft, K is permeability tensor in mD, total mobility (λ_t) and total gravity mobility (λ_g) are defined as:

$$\lambda_t = \sum_{m=1}^{N} \frac{k_{rm}}{\mu_m}, \qquad \lambda_g = \sum_{m=1}^{N} \frac{k_{rm}\rho_m g}{\mu_m} \tag{8}$$

where k_{rm} is the relative permeability of phase m, μ_m is phase viscosity in cp, ρ_m is phase density in lb/ft^3, g is the gravity acceleration constant in ft/s^2, and N is the number of phases. Additionally, we need a transport equation for each phase m as follows:

$$\phi \frac{\partial S_m}{\partial t} + \overrightarrow{u_t} \cdot \nabla f_m + \nabla \cdot \overrightarrow{G_m} = 0 \tag{9}$$

where ϕ is porosity of media in fraction, the total velocity $\overrightarrow{u_t}$ is derived from the 3-D solution to the pressure field (Eq. (7)) and the application of Darcys Law in ft/s. The phase fractional flow term is given by:

$$f_i = \frac{k_{rm}}{\mu_m} / \sum_{i=1}^{N} \frac{k_{ri}}{\mu_i} \tag{10}$$

The phase velocity outcoming from the gravity influence is given by:

$$\overrightarrow{G_m} = Kg\nabla D f_i \sum_{i=1}^{N} \frac{k_{ri}}{\mu_i} (\rho_i - \rho_m) \tag{11}$$

By defining time of flight (TOF), τ, as the time required by a neutral tracer to travel up to a certain location along a streamline as:

$$\tau = \int \frac{\phi}{\|\overrightarrow{u_t}\|} \tag{12}$$

The transport equation can be converted to the streamline coordinate using the following transformation:

$$\overrightarrow{u_t} \cdot \nabla = \phi \frac{\partial}{\partial \tau} \tag{13}$$

Hence, the saturation equation in the porous media can be written along the streamlines as:

$$\frac{\partial S_m}{\partial t} + \frac{\partial f_m}{\partial \tau} + \frac{1}{\phi} \nabla \cdot \overrightarrow{G_m} = 0 \tag{14}$$

These nonlinear governing equations (in terms of pressure and saturation) can be discretized and numerically solved in an iterative approach (Bratvedt et al., 1996).

3.5 Objective function

It is required to define an objective function before submitting an optimization run. The net present value (NPV) is considered as the objective function in all the problems. The objective function is given by:

$$NPV = \sum_{t=1}^{T} \frac{C_t}{(1+d)^t} - C^{drill} \tag{15}$$

where T is the total production time in years, d is the annual discount rate in fraction, C^{drill} is the drilling and completion cost per well within the reservoir in \$, and C_t is cash flow after time t in \$ which can be computed as follows:

$$C_t = p_o^{prod} Q_o^{prod} - p_w^{prod} Q_w^{prod} - p_w^{inj} Q_w^{inj} \tag{16}$$

where p_o^{prod} specifies the price of oil in \$/STB, p_w^{prod} and p_w^{inj} are the costs of produced and injected water in \$/STB, respectively, Q_o^{prod} and Q_w^{prod} are the cumulative oil and water produced in STB, respectively, and Q_w^{inj} is cumulative water injected in STB. Calculating the NPV of each possible solution requires running a streamline simulator and reading the output of the simulation procedure. All simulations are done by means of the FRONTSIM option in the ECLIPSE simulator.

Table 2. Economic parameters used to calculate the NPV.

Economic Parameter	Value
Oil selling price (\$/STB)	100
Water production cost (\$/STB)	5
Water injection cost (\$/STB)	5
Drilling and completion cost per well (\$)	10×10^6
Discount rate	0

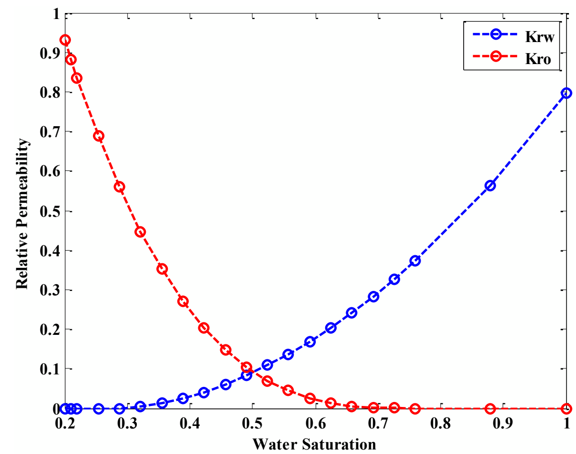

Fig. 2. Oil and water relative permeability.

Table 3. Basic reservoir models properties.

Property	Reservoir Model
Injector BHP (psi)	6,000
Producer BHP (psi)	1,000
Oil viscosity (cp)	1.3
Water viscosity (cp)	0.5
Oil density (lb/ft^3)	55
Water density (lb/ft^3)	62.43
Oil FVF (bbl/STB)	1.04
Water FVF (bbl/STB)	1.005
Rock compressibility (psi^{-1})	4×10^{-6}

The financial parameters utilized to calculate NPV are listed in Table 2.

4. Applications and results

In this section, the GA, the PSO and the suggested hybrid GA-PSO were applied to three different twodimensional reservoir models to compare them in terms of performance. The studied models varied in the size, number of wells, and petrophysical properties. In all examples, the NPV was maximized by determining the optimal locations for vertical wells across a twophase oilwater reservoir undergoing water flooding operation. In all cases, a constant reservoir porosity of 0.25 and heterogeneous permeability distribution were assumed. Initial pressure of the system was 4,000 psi. The oil-water relative permeability curves are shown in Fig. 2. Capillary pressure was neglected in all simulation runs over a period of 10 years. Other simulation parameters are given in Table 3.

4.1 Synthetic case 1

In this case, we consider a heterogeneous synthetic reservoir model with a single injection well in the center, at grid block (14, 14). The model has 27 × 27 × 1 grid blocks, with block dimensions of 100 × 100 × 50 ft. The horizontal distribution of the reservoir permeability is shown in Fig. 3. The permeability field shown in Fig. 3 is just like that Afshari et al. (2011) used in their example cases, however other parts of the problem are changed. Our objective is to optimize the locations of four production wells in this reservoir. There exist two optimization variables for each well (X and Y grid block indices), resulting in a total of 8 variables. These blocks: (1, 1), (27, 1), (1, 27) and (27, 27); are the optimum locations, which the consistent NPV for this global optimum solution is 4.7441×10^8.

For standalone and hybrid runs, the population (or swarm) size is comparable to the number of variables, while the number of iterations and the total number of function evaluations are 50 and 400, respectively. Considering the stochastic nature of these algorithms, each optimization procedure is run five times using various initial guesses. Table 4 shows the results of GA, PSO and HGAPSO algorithms. We see that the highest average NPV is obtained by running HGAPSO algorithm. Fig. 4 presents the arithmetic averages of the five runs versus number of function evaluations for each method. The average NPVs achieved by HGAPSO, PSO and GA are 4.704×10^8, 4.610×10^8, and 4.544×10^8, respectively. Thus, HGAPSO solution has an objective function about 2.039% higher than PSO, and 3.521% higher than GA. Also, it can be seen that HGAPSO worked better than standalone methods in terms of the number of numerical simulations performed to attain the global optimum solution.

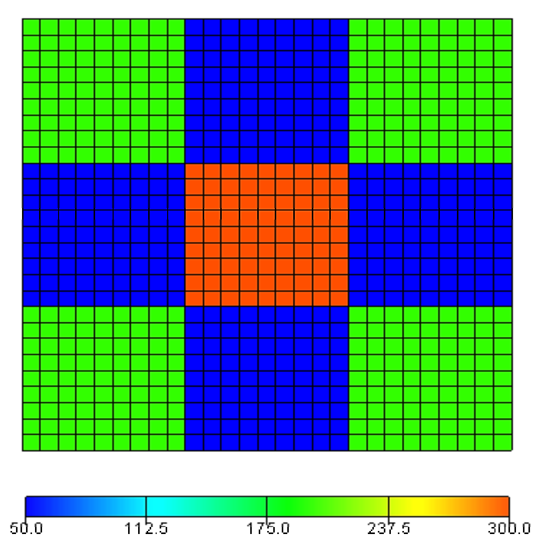

Fig. 3. Permeability distribution for reservoir model of synthetic case 1.

Table 4. Optimization results (NP $\times 10^{-8}$) for synthetic case 1.

	Run 1	Run 2	Run 3	Run 4	Run 5	Average
GA	4.619	4.527	4.323	4.542	4.708	4.544
PSO	4.535	4.616	4.468	4.729	4.703	4.610
HGAPSO	4.680	4.743	4.717	4.718	4.662	4.704

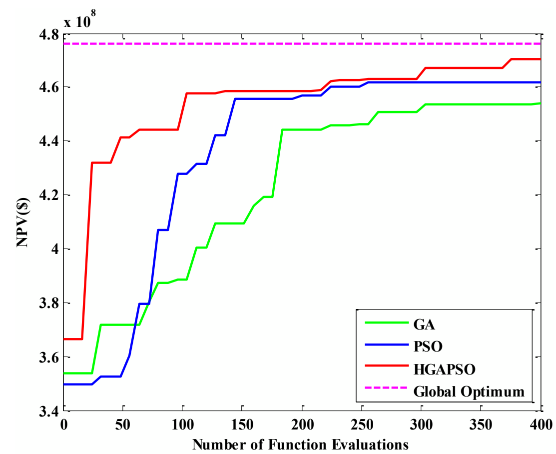

Fig. 4. The progress of optimization process for synthetic case 1.

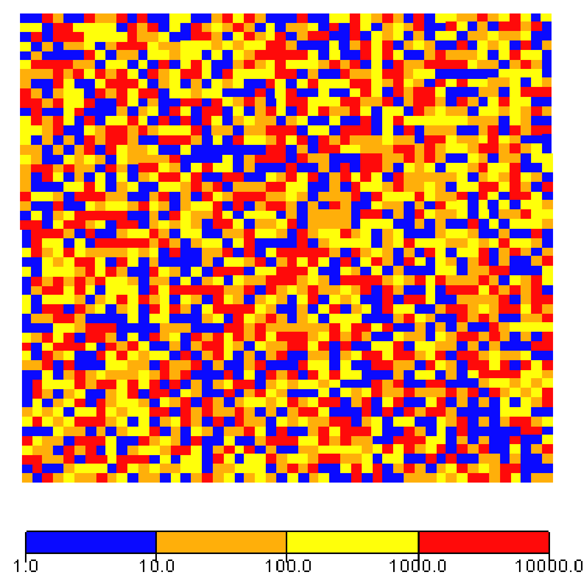

Fig. 5. Permeability distribution for reservoir model of synthetic case 2.

4.2 Synthetic case 2

In this example, we consider a model which has 50 × 50 × 1 grid blocks, with block dimensions of 40 × 40 × 100 ft. Permeability varies from cell to cell and the average permeability is 1,110 mD. The horizontal logpermeability distribution of the reservoir is shown in Fig. 5.

Our objective is to find the place for three production

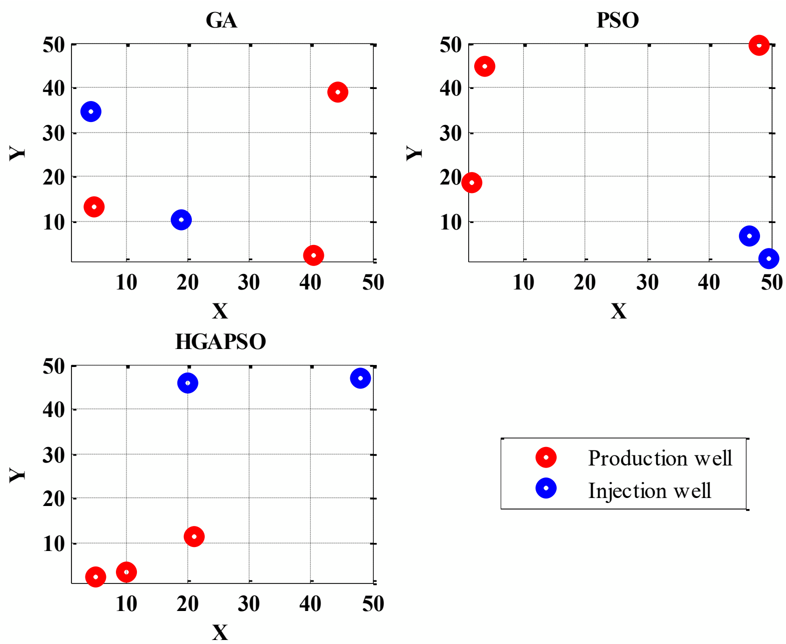

Fig. 7. Optimum location of production and injection wells for synthetic case 2.

and two injection wells in this reservoir. Each well has two optimization variables (X and Y grid block indices), resulting in a total of 10 variables. For standalone runs, the population (or swarm) size is 10 and the number of iterations is also 50, so the total number of function evaluations is 500. For HGAPSO, the maximum number of function evaluations is also set to 500. Each of the three methods is run five times starting from different initial population.

The results have been summarized in Table 5. Fig. 6 displays the progress of mean NPV for the GA, PSO and HGAPSO methods. From this figure, we see that the HGAPSO method outperforms its component methods. The average objective function obtained by HGAPSO, PSO and GA are 6.379×10^8, 6.182×10^8 and 6.064×10^8, respectively. This maximum value achieved by HGAPSO is 3.187% higher than that of PSO and 5.195% higher than that of GA. The best well locations (from the run with the maximum final NPV found by standalone and hybrid algorithms after 500 function evaluations are plotted in Fig. 7. Results of the optimum runs of the algorithms provide the oil saturation maps, which are shown in Fig. 8. It is evident that hybrid solution provides slightly better overall sweep.

Table 5. Optimization results (NP $\times$ 10^{-8}) for synthetic case 2.

	Run 1	Run 2	Run 3	Run 4	Run 5	Average
GA	6.046	6.083	6.027	6.196	5.970	6.064
PSO	6.230	6.251	6.333	5.784	6.314	6.182
HGAPSO	6.385	6.404	6.381	6.347	6.380	6.379

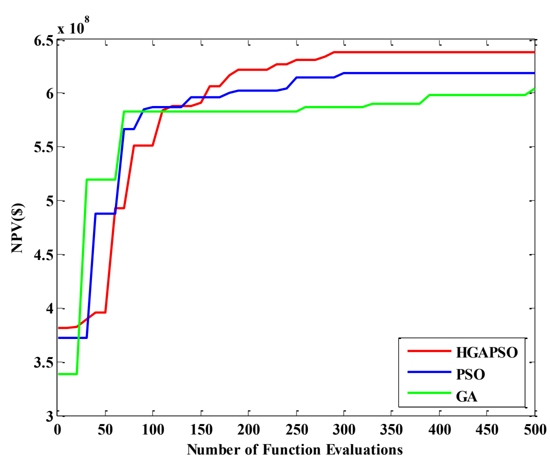

Fig. 6. The progress of optimization process for synthetic case 2.

4.3 Synthetic case 3

We now define the optimum place for four production and two injection wells in a heterogeneous synthetic reservoir model. The model contains $60 \times 60 \times 1$ grid blocks, with each block of dimensions $50 \times 50 \times 50$ ft. The average permeability is 1,100 mD. The horizontal permeability distribution of the reservoir is depicted in Fig. 9. For standalone and hybrid runs, the population (or swarm) size is 12, with 75 iteration numbers, and the total number of function evaluations is 900. It is worth mentioning that each method has been run five times (the results have been summarized in Table 6).

Fig. 10 shows a comparison between the performances of the algorithms, which presents the evolution of the mean NPV throughout the optimization as a function of the number of simulations. This again highlights the superiority of HGAPSO relative to standalone methods in terms of average performance and the best solution collected from five runs. The mean NPV found by HGAPSO, PSO and GA are 8.660 $\times 10^8$, 8.383×10^8 and 8.300×10^8, respectively. Therefore, HGAPSO solution has an NPV about 3.304% higher than

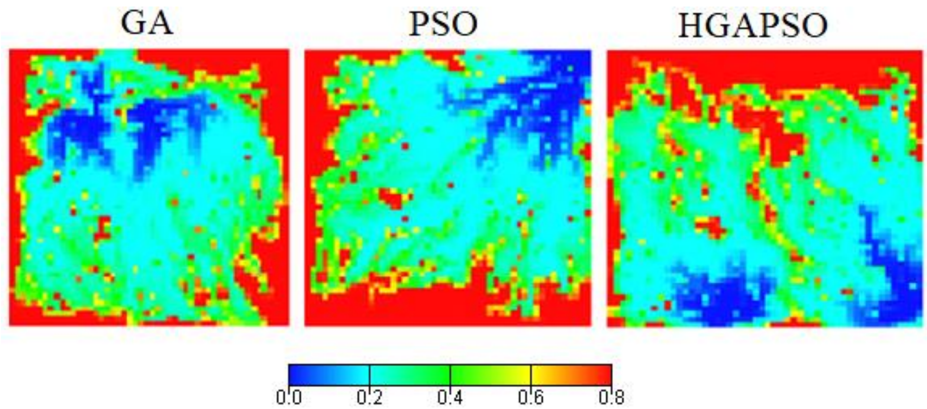

Fig. 8. Oil saturation maps for best optimization runs of GA, PSO and HGAPSO algorithms (case 2).

PSO, and 4.338% higher than GA. Fig. 11 illustrates the distinct arrangements of six wells, which have the maximum NPVs in five optimization runs. Maps of the final oil saturation obtained from optimum solutions for three approaches are shown in Fig. 12. This figure demonstrates the improvement in sweep efficiency of HGAPSO over the GA and PSO methods. In this hybrid procedure, almost all of reserves in the reservoir model is produced.

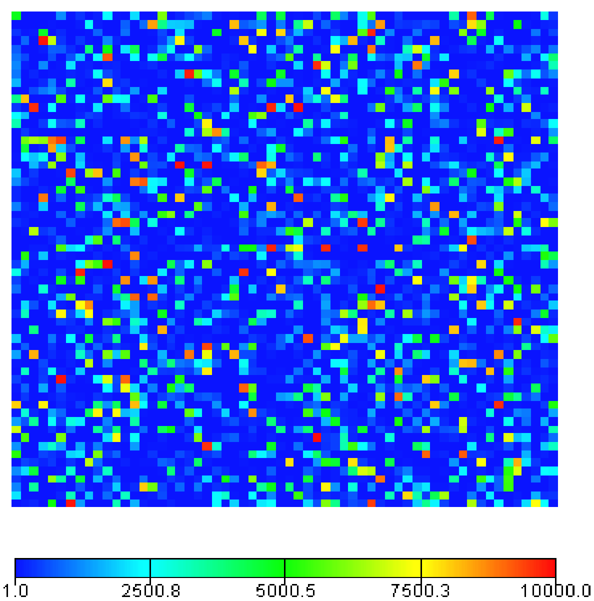

Fig. 9. Permeability distribution for reservoir model of synthetic case 3.

Table 6. Optimization results (NP $\times$ 10^{-8}) for synthetic case 3.

	Run 1	Run 2	Run 3	Run 4	Run 5	Average
GA	8.283	8.294	8.288	8.305	8.326	8.300
PSO	8.375	8.402	8.385	8.394	8.361	8.383
HGAPSO	8.668	8.665	8.651	8.646	8.672	8.660

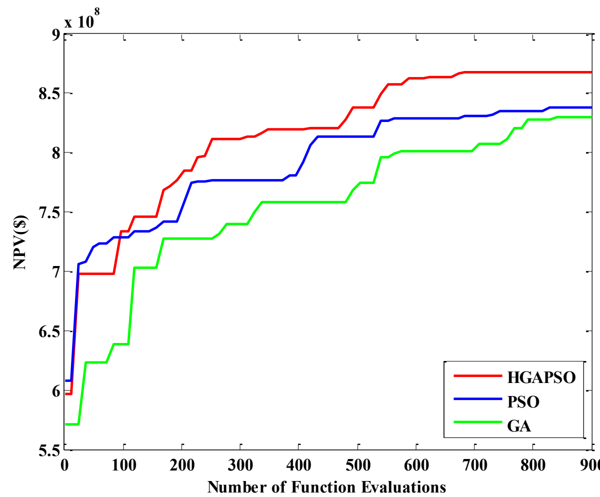

Fig. 10. The progress of optimization process for synthetic case 3.

5. Conclusion

Effectively integrating the exploration ability of the GA with the efficiency of PSO, a hybrid GA-PSO algorithm was implemented for optimal location of wells across oil reservoirs. The performance of the suggested hybrid algorithm was compared with classical GA and PSO through benchmark optimization problems including synthetic reservoir models. In all cases, the proposed hybrid GA-PSO provided comparable or even more reliable results than both GA and PSO. Accordingly, the proposed hybrid GA-PSO provides a practical substitute to the GA and PSO, as two frequently used algorithms for production optimization problems. The use of the hybrid GA-PSO can lead to the design of more efficient production scenarios. Future research works may focus on the application of this novel approach to other practical production optimization problems.

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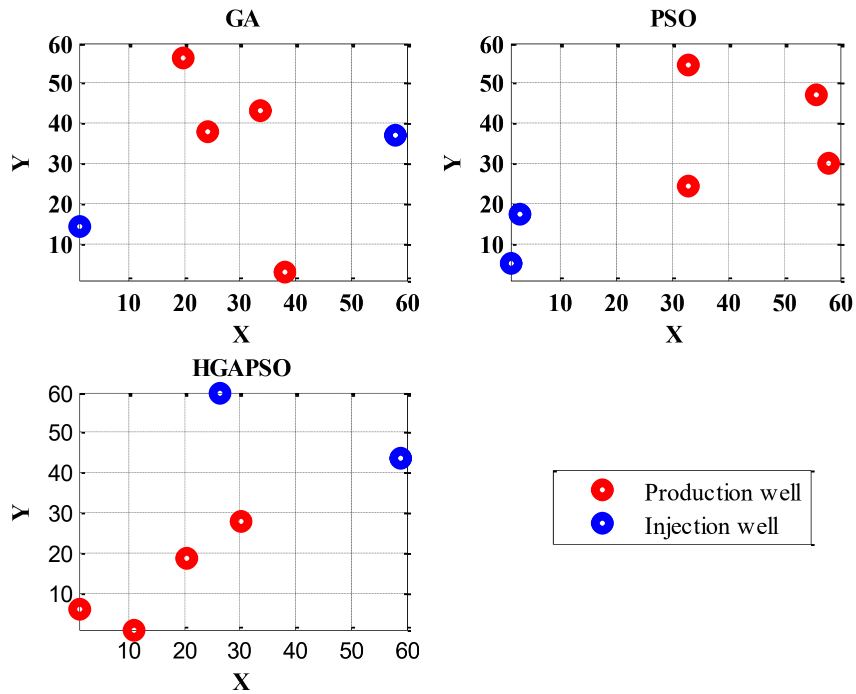

Fig. 11. Optimum location of production and injection wells for synthetic case 3.

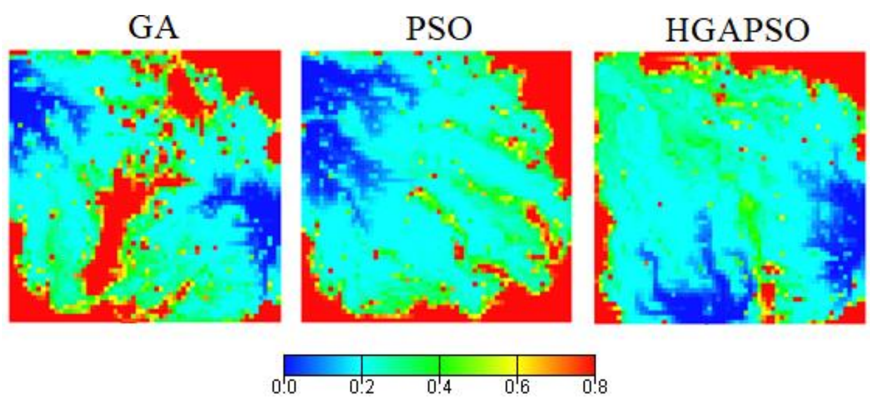

Fig. 12. Oil saturation maps for best optimization runs of GA, PSO and HGAPSO algorithms (case 3).

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