Production Optimization Using an Experimental Design and Genetic Algorithm

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Abstract: In the context of oil production optimization, finding the well parameters that maximize an objective function such as recovery factor or cumulative oil production is an important issue. Reservoir simulation which is coupled with automated optimization algorithms are often employed for this work. However, determining the optimal well design is a complex and challenging problem due to the reservoir heterogeneity, economic criteria and technical uncertainty. Therefore, it is necessary for the development of a powerful and trusted optimization algorithm that can detect best production variables with a minimum required number of simulation runs. This study presents a hybrid approach that employs experimental design and genetic algorithm to determine the optimum well parameters in different models. In this approach, experimental design is used to establish the initial population of solution vectors. The performance of hybrid method has been compared with a standalone genetic algorithm. Results show that the proposed method is a quick and precise approach for the optimization problems compared to the standalone genetic algorithm.
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1. Introduction

Production optimization is a crucial stage in integrated reservoir management which considerably affects the efficiency of an oil reservoir. Several parameters such as optimum number, type, production rate and location of wells should be optimized in an optimization project. In addition, this problem is substantially more complicated if different engineering, geological and economic variables are included. Thus, traditional optimization methods must be evaluate hundreds or even thousands potential scenarios for searching for the optimal solution using numerical reservoir simulations. For this reason, intelligent optimization algorithms are commonly used for this nonlinear and high dimensionally problems that usually contains local optima. The computational algorithms employed for this major divided into two main groups: gradient free or stochastic algorithms and gradient based algorithms.

In gradient based methods, the derivative, or gradient, of the objective function with respect to the control variables is calculated. The most common gradient based optimization algorithms for production optimization are simultaneous perturbation stochastic approximation (Bangerth et al., 2006), finite difference gradient algorithm (Bangerth et al., 2006) and adjoint-based gradient algorithms (Zandvliet et al., 2008). The broad advantage of gradient based methods is that convergence is faster than the gradient free approach. One of the main problems of the gradient based methods is that it often converges to a local optimum of the objective function instead of the global optima.

In contrast to gradient based methods, the gradient free methods do not require the computation of cost function derivatives and use just the objective function values determined by performing function evaluations. Gradient-free methods suitable for use in production optimization can be classified into two categories. The first category consists of deterministic methods such as generalized pattern search (Ciaurri et al., 2011), Hooke-Jeeves direct search (Aliyev, 2011) and Nelder-Mead simplex method (Siemek and Stopa, 2006). The second category including stochastic or global methods such as simulated annealing (Beckner and Song, 1995), genetic algorithm (Bittencourt and Horne, 1997; Montes et al., 2001; Emerick et al., 2009; Morales et al., 2010), particle swarm optimization (Onwunalu and Durlofsky, 2010), harmonic search algorithm (Afshari et al., 2011), ant colony optimization (Razavi and Farahani, 2010) and covariance matrix adaptation evolution strategy (Ding, 2008). The first category is generally very robust, search locally and thus requires fewer function evaluations. Though they are very sensitive to initial guess of variables and can get trapped in local optima. The second category can, in theory, avoid this problem but has the disadvantages of not increasing objective function at each iteration and requiring many forward reservoir simulations (Zandvliet et al., 2008).

Conventionally, reservoir and production engineers perform many simulations for different values of each uncertain parameter. This method, though exact, generally does not take into consideration the possible interactions that exist between the parameters as is common in oil and gas systems. Experimental design overcomes this major limitation and provides a robust approach to assessing uncertainty. The concept of experimental design refers to the process of defining a set of experiments or simulations in a systematic, predefined and statistically correct way (Purwar, 2008).

In order to provide a better explanation and presentation of this research work the paper is divided into the six parts. The second part contains a brief description of the genetic algorithm. In the third part, experimental design methodology is explained. In the fourth part, combination of experimental design and genetic algorithm is described. Then, the hybrid procedure is applied to different case studies including both synthetic and numerical cases, and the result of hybridized method is compared to that of standalone genetic algorithm. The final section summarizes the results of the present work.

2. Genetic Algorithm

The genetic algorithm (GA) is a stochastic computation technique based on the principles of natural evolution and selection which developed by John Holland and his co workers in 1975. GA uses a set of candidate solutions at every iteration. Each of these candidate solutions is called an individual and the collection of individuals is called the population. Conventionally, GA starts its search from the seed (initial population) which generated randomly. GA evaluates the fitness of each individual by obtaining its objective function and the selection operator chooses the individuals with the highest objective function values in the population to be parents, which will produce the next generation of populations. The selection operator simulates the survival of the fittest evolution strategy in nature. After selecting the best individuals as parents, the crossover operator is applied randomly to paired parents to form new population of individuals for the next generation. The crossover operator mimics the mating process that occurs in genetic chromosomes during reproduction. Crossover propagates features of good surviving designs from the current population into the future population, which will have a better fitness value on average. Another major GA operator is the mutation operator. It is analogous to biological mutation. In mutation, a specific element of an individual or solution vector is probabilistically changed to a new value. The purpose of mutation in GA is preventing the algorithm from get stuck in local optima and inserting diversity. GA uses mentioned operators to generate new population from existing individuals. The computations are terminated when the stopping criteria (maximum number of generations, etc.) is satisfied.

2.1 Objective Function

The objective function in this study is undiscounted net present value (NPV) in. The objective function is given by:

$$NPV = p_o^{prod} Q_o^{prod}(x) - p_w^{prod} Q_w^{prod}(x) - C^{drill} \quad (1)$$

here p_o^{prod} indicates the price of oil, p_w^{prod} is the cost of produced water, Q_o^{prod} and Q_w^{prod} are the cumulative oil and water produced (these quantities are obtained from the reservoir simulation output) and C^{drill} is the drilling and completion cost. The economical parameters used to calculate NPV are shown in Table 1.

Table 1. Economic parameters used to calculate the NPV

Economic parameter	Value
Oil selling price ($/STB)	80
Water production cost ($/STB)	20
Drilling and completion cost ($)	5×10^6

3. Experimental Design Methodology

Experimental design methodology is able to select the effective uncertain parameters and to study their effect on the reservoir production with the minimum number of simulator runs (Moeinikia, 2012). A series of design of experiments has been proposed, which aim at maximizing the amount of information from a minimum number of runs. In general, the design of experiments techniques can be classified as classical and space filling design of experiments techniques. The classical techniques were developed for laboratory and field experiments while the space filling design methods relate to deterministic computer simulations. In this study we apply a Latin hypercube design as an efficient space filling design method to generate the initial population of solution vectors.

Latin hypercube sampling (LHS) was introduced by McKay et al., in 1979. Whereas other methods either choice values at limits or predefined levels or produce very large numbers of designs, LHS guarantees that the entire parameter space is represented and the number of experiments is kept intelligently low. The basis of this method is random number generation, which works well with cumulative distribution function (CDF). The CDF of a random variable x can be defined in terms of its continuous probability distribution function f as follows:

$$\mathrm{CDF(x)} = \int_{-\infty}^{x} \mathrm{f(t)dt} \quad (2)$$

For a discrete distribution, the CDF can be expressed as:

$$\mathrm{CDF(x)} = \sum_{i=0}^{x} \mathrm{f(i)} \quad (3)$$

LHS method divides the CDF into a number of equal sections. The same number of sections is applied to each parameter CDF. The sampling process is forced to pick each section with the same frequency. Repeat selections are allowed after all sections have been selected once. In other words, second visit of the section is not permitted until all sections have one visit. For this reason, LHS is considered to be more efficient. The LHS procedure ensures that all parts of the distribution are sampled uniformly.

4. Hybrid Methodology

Hybrid method is a coupled optimization process using a LHS for the initial iterations and a genetic algorithm starting from an automatically selected set of the best cases, i.e., initial population. The Figure 1 shows the generic workflow diagram of this method. A space filling sampling is used to select and simulate N (initial ensemble size) cases. The best L cases are used as starting points for the optimization process. Then, they will be written in a text file to be supplied to reservoir simulator (Eclipse). In the next step, reservoir simulator is run with the supplied settings. Once the simulation run is finished, the GA reads the simulated parameters, i.e. cumulative oil production and cumulative water production in this problem, and calculates the objective function. These steps are repeated for each individual in the population before the selection process takes place. Once all individuals are simulated, the GA sorts these individuals based on their objective function values and then selects the individuals that will contribute to the creation of the next generation. GA operators such as crossover and mutation are applied to the selected individuals to form the next generation. The whole process is repeated for the next generations until termination criteria are met.

5. Results

In this part, the algorithms described in the previous sections are applied to different examples. Results for standalone and hybrid algorithms are presented.

5.1 Numerical Test Example

In this section, the performance of the standalone GA and hybridized method are evaluated using a multi dimensional benchmark optimization problem that contains multiple local optima. This problem is a minimization problem. The optimization problem (Griewangk function) is specified as follows:

$$J(x) = \sum_{i=1}^{8} \frac{x_i^2}{4000} - \prod_{i=1}^{8} \left(\frac{\cos(x_i)}{\sqrt{i}}\right) \quad (4)$$

Subject to: $-10 \le x_j \le 100$, $i = 1, 2, 3 \ldots 8$, the global minima: $x^* = (0\ldots 0)$, $J(x^*) = 0$

First, in order to show the effect of the initial population on the optimization procedure, the GA is run (Table 2 summarizes the genetic algorithm parameters) with four different (random) initial population. Each curve illustrates the average convergence for 900 separate runs of a GA. As shown in Figure 2, the differences in the best objective function values are quite significant. This indicates that the initial population has a phenomenal effect on the performance of a GA. For hybrid algorithm, the space filling design is used to select 60 cases (initial ensemble size). The best cases in the ensemble are then used as an initial population in GA search. It is also obvious that the hybridized GA with experimental design (GA-ED) gives better results compared with a standalone GA.

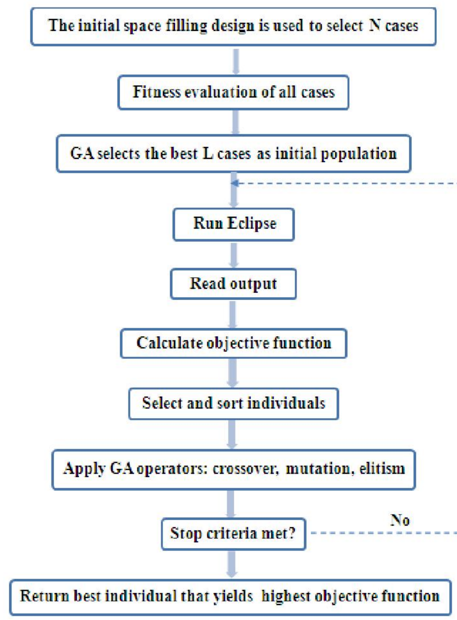

Figure 1. Flowchart for combination of experimental design and genetic algorithm

Table 2. Genetic algorithm parameters

Economic parameter	Value
Population size	30
Crossover probability	0.9
Mutation probability	0.05
Selection scheme	Rank based

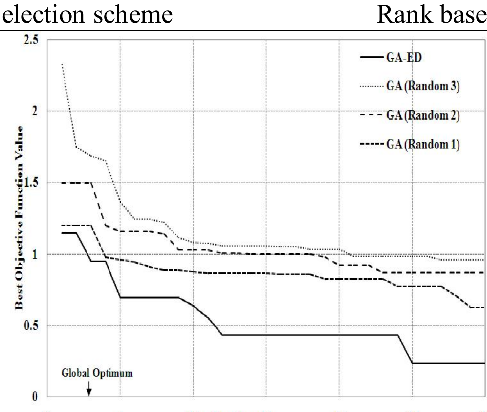

Figure 2. The performance of a genetic algorithm for Griewangk function

5.2 Injection Well Location Optimization in a Homogenous 5-Spot Pattern

The reservoir model used for this problem is shown in Figure 3. The model contains 50×50 grid blocks, with each block of dimensions 20×20×50 ft^3.The properties of the reservoir are shown in Table 3. Four oil production wells are located in the four corners of the reservoir. Standalone GA and hybridized GA with experimental design methodology are used to find the optimum location of one injection well in this model. So, each individual in the GA consist of 2 variables as x and y to indicate the two dimensional location of the injection well. After each individual is simulated, the relevant objective function (NPV) can be calculated. Economic parameters used to calculate NPV have been summarized in Table 1. For standalone runs, the GA population size is 5 and the number of iterations is also 30, so the total number of function evaluations is 150. The GA is run (Table 4 summarizes the genetic algorithm parameters) with four different initial population. For hybrid algorithm, the maximum number of function evaluations is also set to 150. For hybrid algorithms, the space filling design is used to select 40 cases (initial ensemble size). Simulator is run for 40 function evaluations and the best cases in the ensemble are then used as an initial population in GA search. The global optimum well location occurs at x=25 and y=25. The corresponding optimal NPV is $7×107.

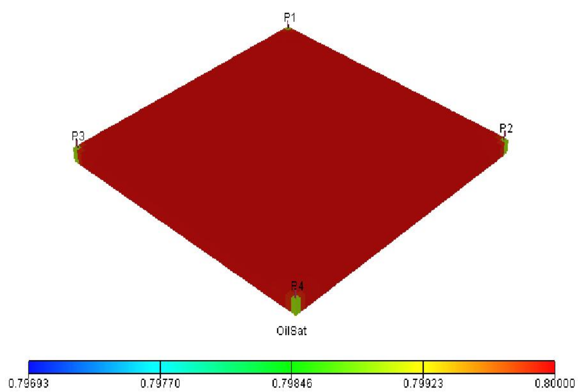

Figure 3. Reservoir model

Figure 4 presents results for standalone GA and Figure 5 represents the results for hybrid method and the arithmetic averages of the different standalone GA runs. As it can be observed in Figure 5, On average ,GA has found the optimum location for the injection well after 150 function evaluations, yielding the well coordinate at x=25 and y=25 (i.e., center of reservoir) and hence confirming the maximum performance of five spot pattern.

Table 3. Basic reservoir properties

Economic parameter	Value
Initial pressure (psi)	4800
Porosity	0.2
Permeability (milli Darcy)	200
Oil density (lb/ft^3)	55
Water density (lb/ft^3)	62.43
Injection well pressure (psi)	5000
Production well pressure (psi)	1000
Simulation time (day)	100

Table 4. Genetic algorithm parameters

Economic parameter	Value
Population size	5
Crossover probability	0.9
Mutation probability	0.05
Selection scheme	Rank based

As shown in Figure 5, it can be seen the hybrid method perform better than standalone GA in terms of the number of function evaluations required to attain the optimum solution. In this example, in the 76th function evaluations, the GA-ED solution achieves the global optimum, while the GA achievement of this optimum after the 150th function evaluations. This example demonstrates the importance of running GA after experimental design.

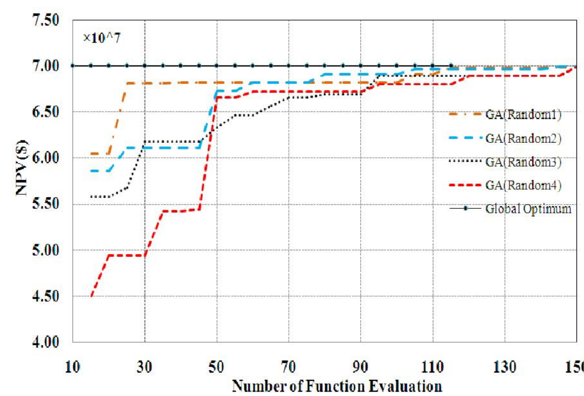

Figure 4. The performance of a genetic algorithm with different initial population

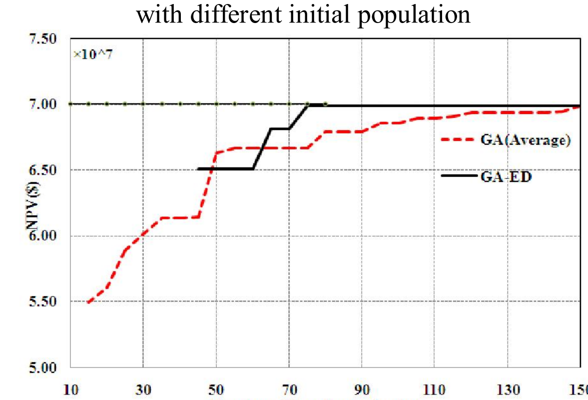

Figure 5. The progress of optimization process

5.3 Single Well Model

The single well model used in this case is shown in Figure 6. Porosity varies from cell to cell; the average porosity is 0.14. The objective function is maximized by determining the completion interval (1-50) in Z-coordinates and bottomhole pressure (BHP) (100<BHP<initial pressure) of the production well. For standalone runs, the GA population size is 5 and the number of iterations is 30, so the total number of function evaluations is 150. The GA is run (the algorithmic settings are the same as in the previous case) with three different initial population. For hybridized method, the maximum number of function evaluations is also set to 150. For hybrid algorithms, the space filling design is used to select 50 cases (initial ensemble size). The simulator is run for 50 function evaluations and the best cases in the ensemble are then used as an initial population in GA search.

Figure 7 presents results for standalone GA. Figure 8 represents the results for hybrid method and the arithmetic averages of the different standalone GA runs. It is apparent from Figure 8 that the hybrid method outperforms the standalone GA in terms of both efficiency and the quality of the final solution. This validates the hybridization idea of starting with a robust space filling design for initial exploration of the solution space and then using a more efficient global search algorithm to quickly converge to an optimal solution.

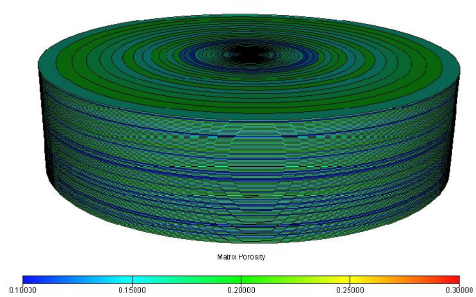

Figure 6. Single well model

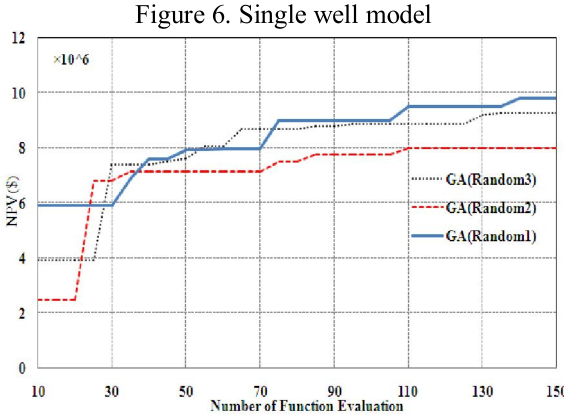

Figure 7. The performance of a genetic algorithm with different initial population

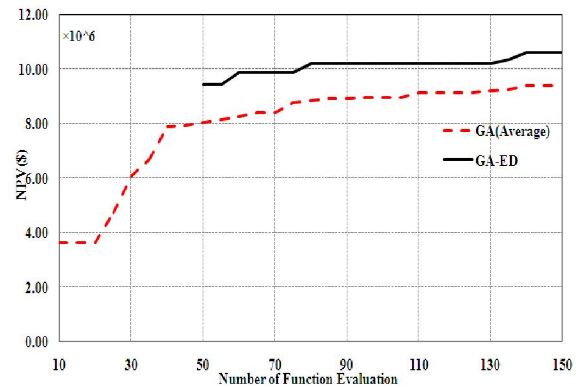

Figure 8. The progress of optimization

6. Conclusions

Based on the results obtained from this study the GAs are seed dependent algorithms. Fitter initial population are more possible to generate superior solutions and also the optimization processes require less function evaluation.

Space filling design methodology covers the whole uncertainty available in the system with the minimum number of simulation runs. Actually, this method, as an unbiased approach, has the potential of adding valuable information to the reservoir development plan and also, of saving considerable time.

In this study, a novel hybrid method which consists of two parts, first part with space filling design and the second phase with the genetic algorithm were investigated for optimization problems. The results of this study shows that by direct employment of experimental design methodology with genetic algorithm, one can get the precise results with the least number of simulation runs instead of running the simulator several times in a genetic algorithm with randomly initialization. This increase in GA performance occurs because it directs the search toward the global optimum.

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