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Optimizing Well Placement with Genetic Algorithms: A Case Study

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Abstract

Maximizing the net present value (NPV) of oil field development is heavily dependent on optimizing well placement. The traditional approach entails the use of expert intuition to design well configurations and locations, followed by economic analysis and reservoir simulation to determine the most effective plan. However, this approach often proves inadequate due to the complexity and nonlinearity of reservoirs. In recent years, computational techniques have been developed to optimize well placement by defining decision variables (such as well coordinates), objective functions (such as NPV or cumulative oil production), and constraints. This paper presents a study on the use of genetic algorithms for well placement optimization, a type of stochastic optimization technique that has proven effective in solving various problems. The results of the study show significant improvements in NPV when using genetic algorithms compared to traditional methods, particularly for problems with numerous decision variables. The findings suggest that genetic algorithms are a promising tool for optimizing well placement in oil field development, improving NPV, and reducing the risk of project failure.

Keywords: Well Placement, Optimization, Genetic Algorithm, Infill Drilling.

تحسين تحديد مواقع الآبار باستخدام الخوارزميات الجينية: دراسة حالة

الخلاصة:

يعتمد تعظيم القيمة الحالية الصافية (NPV) لتطوير حقول النفط بشكل كبير على تحسين مواقع الآبار. تتضمن الطريقة التقليدية استخدام الحدس والخبرة لتصميم الآبار وتحديد مواقعها، يتبع ذلك إجراء تحليل اقتصادي ومحاكاة للمكامن لتحديد الخطة الأكثر فعالية. ومع ذلك، غالبًا ما تكون هذه الطريقة غير كافية بسبب تعقيد المكامن. في السنوات الأخيرة، تم تطوير تقنيات حاسوبية لتحسين مواقع الآبار من خلال تحديد المتغيرات لاتخاذ القرار (مثل إحداثيات الآبار)، ووظائف تحديد الاهداف (مثل القيمة الحالية

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الصافية أو الإنتاج التراكمي للنفط)، والقيود. يقدم هذا البحث دراسة حول استخدام الخوارزميات الجينية لتحسين مواقع الآبار، وهي نوع من تقنيات التحسين العشوائي التي أثبتت فعاليتها في حل مجموعة متنوعة من المشكلات. أظهرت نتائج الدراسة تحسينات كبيرة في القيمة الحالية الصافية عند استخدام الخوارزميات الجينية مقارنة بالطرق التقليدية، خاصة في المشكلات التي تحتوي على العديد من متغيرات القرار. تشير النتائج إلى أن الخوارزميات الجينية أداة واعدة لتحسين مواقع الآبار في تطوير حقول النفط، مما يساهم في تحسين القيمة الحالية الصافية وتقليل مخاطر فشل المشاريع.

1. Introduction

Infill drilling is a reservoir management strategy aimed at improving sweep efficiency by inserting additional wells that are spaced closer together, thereby reducing the average well-spacing. This technique enhances connectivity between injectors and producers, leading to improved reservoir economics [1-6]. The placement of infill wells is expected to target areas within the formation that have high oil saturation, thereby increasing the rate of field recovery. However, the process of drilling a large number of wells is complicated by the need to select the optimal location for each well to maximize recovery acceleration [7-10] .

The process of infill well drilling involves studying a wide range of variables, including geological, well configuration, economic, and production variables [11]. Infill drilling aims to add incremental reserves to existing ones or accelerate production from depleted areas. Prediction of incremental and accelerated recovery is crucial for optimizing infill wells and ensuring long-term economic sustainability. Various techniques have been proposed for estimating incremental and accelerated recovery based on readily available production data. Optimization of well paths, types, and drilling order can maximize the net present value (NPV) of production over the life of the reservoir. Genetic algorithms (GA) combined with stochastic simplex approximate gradient (StoSAG) have been used to find the optimal choices of drilling paths, types, and drilling order [12]. Well pattern infilling is evaluated as a productivity construction project, considering economic standards for infilling feasibility and increased recoverable reserves [13]. In developed fields, it is even more difficult to determine infill well locations because of the heterogeneity of the formation in addition to the many existent wells.

The current industry practice is to use the intuitive judgment of skilled petroleum engineers to design various oil well configurations and locations, and then perform economic analysis and simulation of the reservoir model on the worked plan to find the most effective one [14, 15]. Additionally, evolutionary identification of convolutional neural networks is used for automated seismic analysis to estimate reservoir characteristics for optimal well allocation. Furthermore, a new customized method has been developed to analyze intersections of qualities that form proper

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characteristics of good oil and gas wells, resulting in better production profiles [16]. These advancements in intelligent approaches and optimization techniques aim to improve the efficiency and effectiveness of well design and location decisions in the petroleum industry[17, 18].

Due to the complexity and nonlinearity of the reservoirs, it is doubtful that an intuitive well placement design is the most effective solution to the problem at hand. This facilitates the use of optimization techniques to tackle the problem of optimizing well placement[19].

The task of well placement optimization is challenging because production capacity evaluation of numerous wells may be demanded. With each evaluation, a simulation run is required; and for large or complex reservoir models, the simulation run time can be excessive. The amount of simulation runs required depends on the variables of optimization, the search space size, and what optimization algorithm is implemented.

The importance of optimizing well placement in maximizing the net present value (NPV) of oil field development has been highlighted in the preceding discussion. Traditional approaches often fail to address the complexities of reservoirs, resulting in suboptimal results. In contrast, this paper proposes genetic algorithms as a promising computational technique for improving well placement strategies. The following sections will provide an in-depth analysis of the methodology, case study, and results. The study presents valuable insights into the potential of genetic algorithms for enhancing NPV and mitigating risk in oil field development projects.

2. Theory of Well Placement Optimization

This kind of optimization problem is very time-consuming as a huge amount of simulation runs need to be done, [19]. Therefore, there has been a growing need for a rapid and robust approach to untangle this problem.

Optimization techniques that have been used to address WPO problems can be classified into two sets: (a) conventional methods, (b) non-conventional methods, as shown in (Figure 1).

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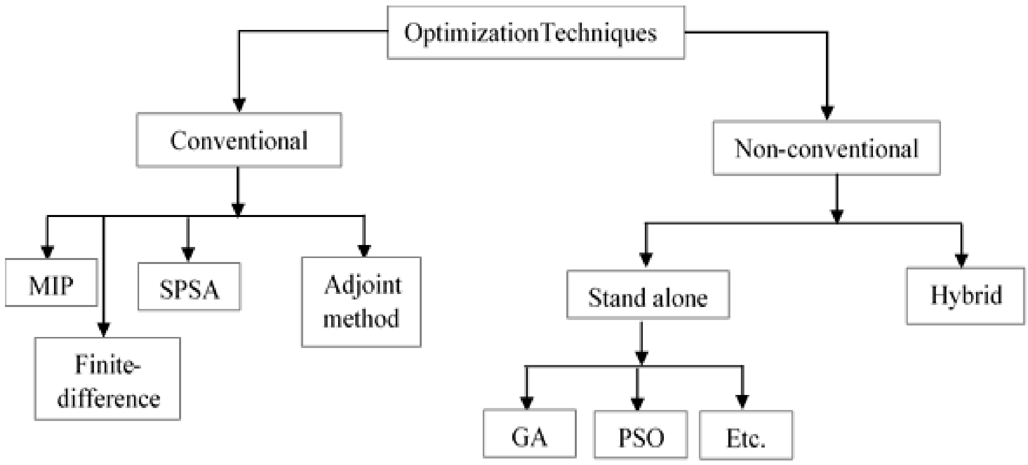

Fig. (1): Optimization techniques used in the well placement problem.

Conventional methods include Mixed-integer programming, implemented Simultaneous perturbation stochastic approximation, Gradient-based finite difference method, Adjoint method. These gradient-based techniques, however, are at risk of getting stuck in locally optimal solutions; therefore, gradient-based techniques are not practical in the WPO problem.

Derivative-free optimization methods have shown satisfactory performance in solving optimization problems where optimization derivatives are difficult to obtain or not available. Gradient-free methods include particle swarm optimization (PSO), differential evolution (DE), ant colony optimization (ACO), genetic algorithm, artificial bee colony (ABC), CMA-ES, bat algorithm (BA), harmony search [20], cuckoo search (CS), etc. Direct mapping of productivity potential, which is a new method, was employed by other researchers and it contributed to an increase in NPV. Hooke Jeeves Directed Search (HJDS) and generalized-pattern search (GPS), which are local search algorithms, have also been used.

Non-conventional gradient-free optimization techniques are less likely to become trapped in a local optimal solution since they do not require derivative calculation [21-23]. However, global optimization algorithms infrequently get stuck in local optimal solutions. Accordingly, combining both local search and global search could be a more improved approach.

3. Genetic-Algorithm (GA)

Genetic algorithm is a statistical technique that was encouraged by the concept that only fit and strong generations survive in nature [24]. In 1975, Jhon Holand published the mathematical basis of GA. Executing GA includes initialization of chromosomes (population) firstly, after which a

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new group of chromosomes is created depending on the fitness value. GA begins the process randomly, then a continuous execution of crossover, mutation, and recombination procedure is done. This process is repeated up to the point that a single best solution is reached [25, 26]. Generally, GA can detect global optima. However, sometimes it shows slow convergence. In practice, Genetic Algorithms (GA) have demonstrated excellent performance in various oil and gas applications, including optimizing oilfield development schemes[27], infill drilling[11], artificial lift [20, 28-30], machine learning models for ROP prediction [31], and reservoir characterization[32].

3.1 Calculation

The genetic algorithm process involves several steps, including initialization, fitness assignment, selection, crossover, and mutation, which are repeated until a termination condition is met and the optimal solution is obtained [5, 33]. The advantages of genetic algorithms include their ability to manage large data sets, they usually don’t require detailed knowledge about the problem, their ability to be parallelized in computer clusters, and their superiority to other traditional feature selection methods [34, 35]. The steps of the GA procedure can be briefed in the subsequent steps and as in (Figure 2).

1. Initially, the genetic algorithm generates an initial population of chromosomes, with each chromosome representing the well coordinates in the well placement problem.
2. The fitness function in the well placement problem is evaluated based on the net present value (NPV) function, which is a function of the well coordinates.
3. The values of well coordinates corresponding to the highest NPV values are selected for reproduction.
4. Using the crossover and mutation processes, a new population of chromosomes is generated with updated well coordinates.
5. The NPV of the new population is then computed.
6. If the solution reaches the maximum number of iterations or reaches the convergence threshold (1%), the optimal solution has been achieved.
7. If not, the cycle of selection, crossover, and mutation is repeated until the termination criteria are met.

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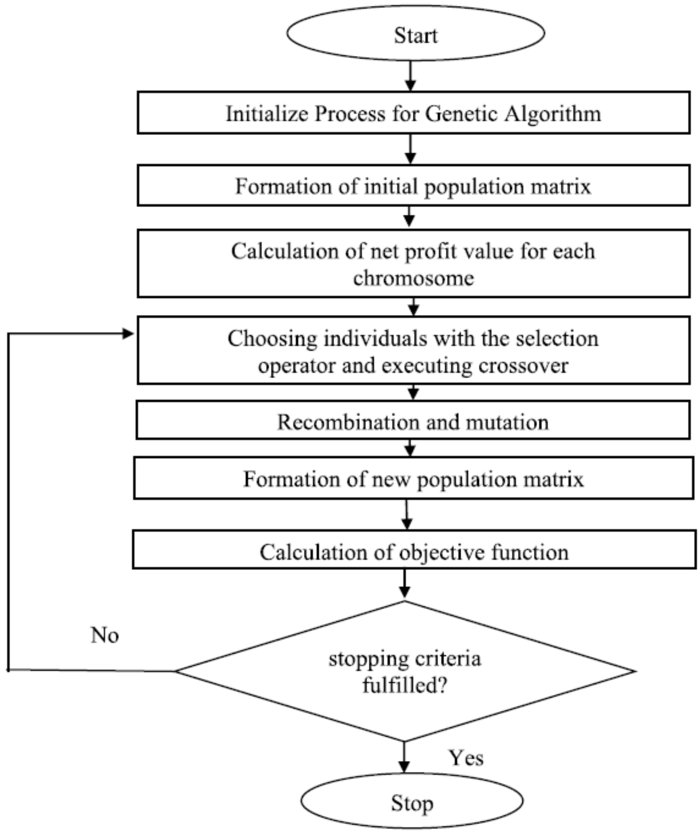

Fig. (2): Genetic algorithm process flowchart

4. Results and Analysis

GA was used to search for optimum well coordinates to maximize the objective function, NPV. Table (1) lists the parameters used to implement the GA technique for this study.

Table (1) Genetic algorithm parameters.

Parameter	Value
Population size	40
Maximum number of generations	10
Selection method	Roulette wheel
Mutation probability	0.05
Maximum number of simulations runs	350
Convergence threshold	1%

4.1 Optimization of Well Coordinates

To set up the model, the Np and NPV are considered as objective functions, while the well coordinates are considered as decision variables. The well coordinates are assumed to be constrained by the reservoir model boundary, production wells, and injection wells by a distance

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(tolerance) of two hundred meters. The maximum allowable number of reservoir simulation runs is limited to 350 runs to terminate the optimization process if the convergence criteria are not met. This number is set based on the researcher's experience running many simulations and the practical feasibility. In the last two scenarios, four hundred runs were set as the limit.

Genetic algorithm was applied in this study. This method is selected because it is the most broadly implemented derivative-free optimization algorithm classically used in petroleum engineering, reservoir simulation, and statistics [36-39].

The PETREL / ECLIPSE commercial numerical reservoir simulator (Schlumberger, 2020a, 2019b) is considered to be the standard and most widely used numerical simulator in the petroleum industry. This simulator is used for this study. The total simulation runs count that was conducted to assess the performance of all four optimization techniques is 4509 numerical simulation runs.

4.2 Base Case

Initially, a base case simulation was conducted without the insertion of infill wells to compute the reservoir's net present value (NPV) and Np. This step was performed prior to implementing the optimization technique to enable comparison before and after the addition of infill wells. The development strategy was set for a 10-year period from January 1st, 2020, to January 1st, 2030, which was used for all subsequent scenarios. The results of the base case simulation are presented in Table (2).

Table (2): Base case run results.

Case	Np (STB)	NPV($)	Period
Base	117,043,673	5,218,457,093	10 years

Three optimization scenarios were completed by setting a different number of infill wells in the sector model.

Table (3) Optimization scenarios and the number of infill wells for each scenario.

Scenario	Number of infill wells	Decision variables
Scenario I	One well	2
Scenario II	Three wells	6
Scenario III	Five wells	10
Scenario IV	Seven wells	14

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4.3 Development Scenarios:

Scenario I

In this scenario, only one infill well was considered for the development strategy of the selected oilfield, and its coordinate was determined by the previously mentioned optimizer. The optimizer proposed well's coordinates, cumulative oil production, and NPV for each simulation run.

Scenario II

In this scenario, three infill wells were considered for the development strategy of the selected oilfield, and their coordinate was determined by the optimizer.

Scenario III

In this scenario, five infill wells were considered for the development strategy of the selected oilfield, and their coordinate was determined by the optimizer.

Scenario IV

In this scenario, seven infill wells were considered for the development strategy of the selected oilfield, and their coordination was determined by the optimizer.

Table (4) Results of the global optimum Net Present Value of all scenarios for the applied optimization method.

Scenario	Optimization Method	NP (STB)	NPV (MM $)
I	GA	147,344,236	5,972.204
II	GA	168,572,553	6,832.637
III	GA	192,100,616	7,786.284
IV	GA	214,524,473	8,695.175

Figure (3). Below shows the NPV values from the first optimization scenario (One infill well) illustrated as a surface.

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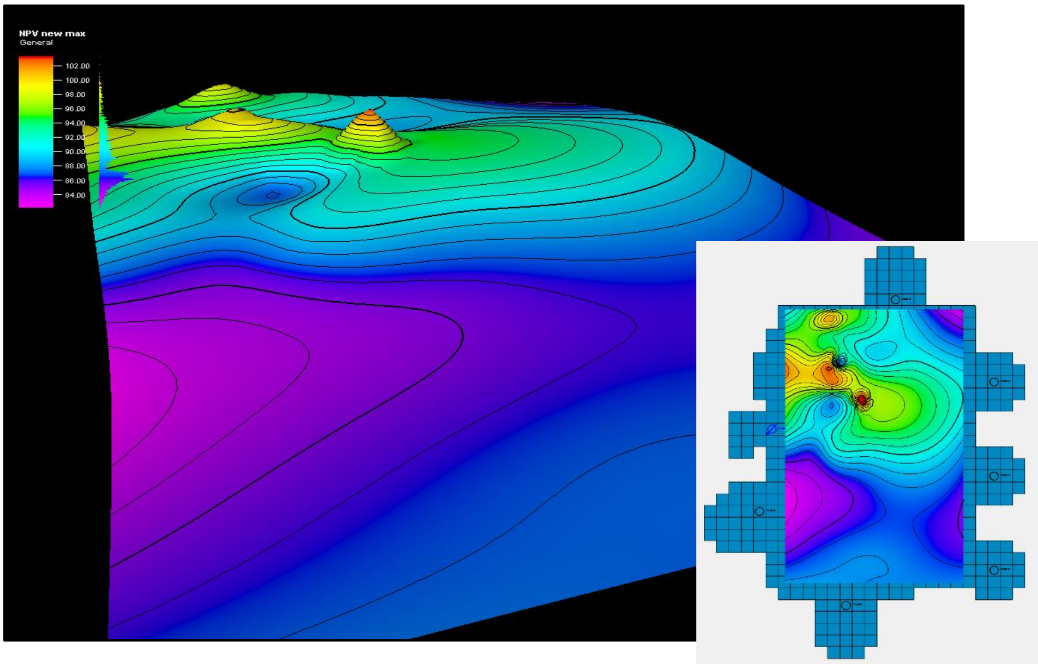

Fig. (3): Net present values illustrated as a surface.

4.4 Discussions

As described earlier, 809 numerical simulation runs are conducted to evaluate the performance of GA. Results obtained from the first scenario (addition of one infill well) for both NPV and Np showed that the genetic algorithm provided the optimum solution in a quite low time-consuming scenario.

Furthermore, the superiority of GA is quite evident in the second, third, and last scenario with a considerable increase in NPV and Np of GA outcome with a very efficient time-consuming scenario as shown in Figure (4).

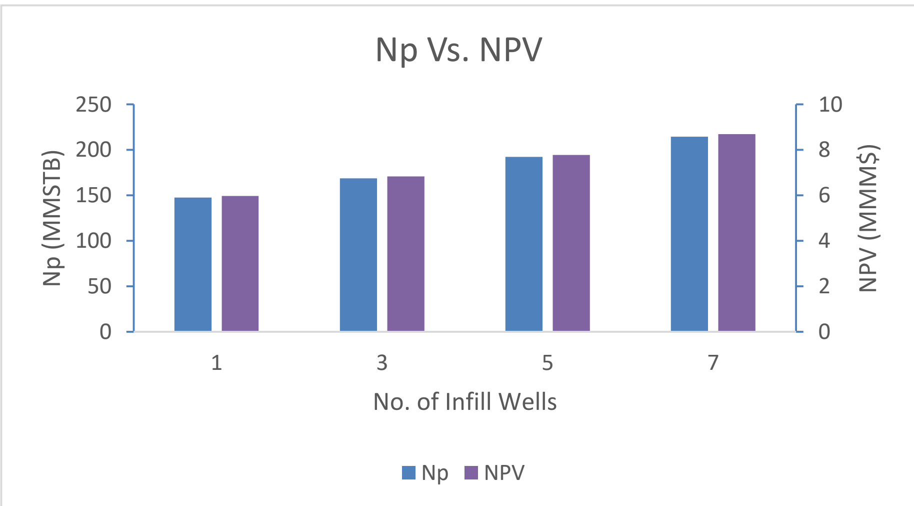

Fig. (4): 1 N_P, NPV for GA optimization method for various scenarios

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Figure (5) shows that genetic method is not influenced by the number of decision variables because the same number of reservoir simulation runs are required under a different number of decisions variables. This is a huge advantage for GA over various optimization techniques.

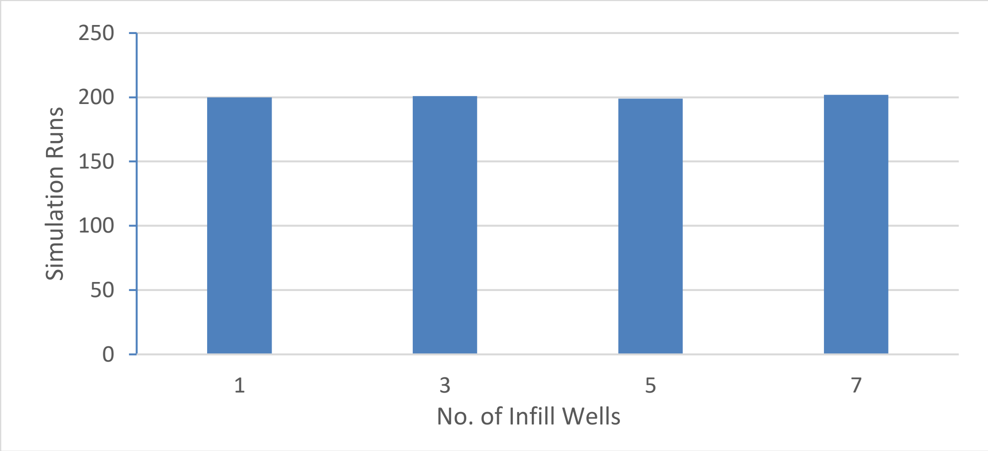

Fig. (5): Number of Simulation runs of GA for each scenario.

5. Conclusions

1. Several optimization techniques can be employed to optimize infill well locations. The identification of the most efficient optimization technique is critical, especially from economic, resource, and time constraint viewpoints.
2. From a time-consuming viewpoint, various optimization methods are variable dependent. As the decision variables start to increase with the increasing number of infill wells, these methods begin to take a greater number of simulation runs to converge, this number of simulation runs required by these techniques is directly proportional to the number of decision variables.
3. GA on the other hand is not influenced by the number of decision variables because the same number of reservoir simulation runs are required under a different number of decision variables.
4. The GA optimization technique was generally found to be very effective and time-efficient to optimize well locations to reach maximum NPV in well placement optimization problems that have a range of number of decision variables.

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