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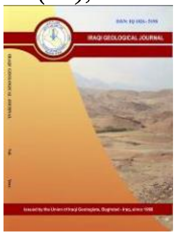

A Survey of Infill Well Location Optimization Techniques

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Abstract

The maximization of the net present value of the investment in oil field improvements is greatly aided by the optimization of well location, which plays a significant role in the production of oil. However, using of optimization methods in well placement developments is exceedingly difficult since the well placement optimization scenario involves a large number of choice variables, objective functions, and restrictions. In addition, a wide variety of computational approaches, both traditional and unconventional, have been applied in order to maximize the efficiency of well installation operations. This research demonstrates how optimization approaches used in well placement have progressed since the last time they were examined. Following that, the research looked at a variety of different optimization strategies, and it demonstrated the limitations of each strategy as well as the scope of its application in order to achieve a suitable level of accuracy and simulation run time. In conclusion, this study presents an all-encompassing analysis of the well location optimization approaches that are applied in the petroleum engineering area, ranging from traditional methods to contemporary methods that make use of artificial intelligence.

Keywords: Optimization; Reservoir simulation; Infill well drilling; Well placement

1. Introduction

In recent years, there has been a growing need for the development of petroleum reservoirs via the construction of infill wells to drain oil areas that are not being produced enough by wells that are already in operation. All of the actions that are associated with drilling a wellbore to intercept one or more predetermined spots constitute what is known as "well placement." The phrase is often used to wells that are either horizontal, vertical, or directional in orientation, and which are designed to maximize contact with the most productive areas of the reservoir (Mahmood and Al-Fatlawi, 2022). The scope of infill wells drilling is to raise the recovery factors from wells, that have bypassed high oil and gas saturation regions (Dheyauldeen et al., 2021). The optimization strategies that have been used to solve Well Portfolio Optimization(WPO) issues may be divided into two categories, namely the following: (a) approaches that are considered traditional, and (b) methods that are considered unconventional. The determination of the locations of infill wells and the optimal spacing between them is an essential component of optimal reservoir management. This component, along with the maximization of corresponding incremental field production and, as a consequence, the profitability of the project, is also important. This is due to the fact that having a large well spacing will, as a consequence, allow part of

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the hydrocarbon-bearing sands to not be swept as effectively (Dheyauldeen et al., 2021). When there is insufficient distance between wells, some of the sands that contain hydrocarbons will be penetrated by more than one well. This will result in interference and a reduction in the amount of fluid that is drained by the producing wells. However, optimizing the location of infill wells may be a difficult job due to the fact that it may be necessary to anticipate the production capacity of a large number of wells, and each assessment may call for a simulation run due to the complexity of the underlying reservoir model. The time needed to conduct a simulation might sometimes result in high computational costs(Annan Boah et al., 2019). The amount of simulations that need to be done is mostly determined by the number of optimization variables, the size of the search space, and the kind of optimization technique that is being used. Because of this, adopting a development plan is not enough to ensure effective petroleum reservoir exploitation and management; rather ,(Dheyauldeen et al., 2022) a strategy that is more integrated and all-encompassing is necessary. Various methods of optimization have been tried and tested in an effort to locate the most productive well sites within a petroleum reservoir(Agbauduta, 2014). When it comes to drilling in-fill wells, determining the optimal number of wells to dig and where to position them inside the reservoir is one of the most difficult and important challenges that arise. The solution to this issue depends on a number of factors, some of which include geological considerations, well configurations, production variables, and economic considerations. The identification of an appropriate development plan for a particular field is made more challenging by the presence of all of these factors as well as the geological unpredictability of the reservoir. This is because the design must analyze hundreds or thousands of different infill possibilities(Annan Boah et al., 2019).

2. Optimization Techniques

The optimization methods that are used for resolving issues related to well location may be broken down into two primary groups: global search stochastic algorithms (gradient-free) and gradient-based algorithms(Yeten et al., 2003). Calculating the objective function's gradients is a necessary step in the implementation of a gradient-based optimization method. It is possible to calculate the gradients either numerically or by utilizing adjoint techniques. In gradient-based algorithms, the objective of each iteration is to enhance the values of the objective function by progressing in the right search direction. Therefore, algorithms that are based on gradients are computationally efficient, despite the fact that they are prone to get stuck in local optima. Furthermore, the lack of analytical solutions in most cases, the nonlinearity and noncontinuity of oil field optimization problems tend to limit the utilization of standard gradient-based optimization methods (Agbauduta, 2014). Optimization techniques that have been used to address WPO problems can be classified into two sets: (a) conventional methods, (b) non-conventional methods.

2.1. Conventional Methods

Recent times have seen a proliferation of optimization strategies being put into action. A summary of the most frequent occurrences is provided in the following parts of this article.

2.1.1. Simultaneous-perturbation-stochastic-approximation

One kind of stochastic approximation approach is known as the SPSA. This technique provides a reasonable methodology for estimating the gradient even when the ideal value is located a great distance away(Mahmood and Al-Fatlawi, 2021).

One optimization method that has attracted considerable international attention is the simultaneous perturbation stochastic approximation (SPSA) method. As motivated above and like methods such as simulated annealing or genetic algorithms SPSA uses only objective function measurements. This contrasts with algorithms requiring direct measurements of the gradient of the objective function (which are often difficult or impossible to obtain). Further, SPSA is especially efficient in high-dimensional problems in terms of providing a good solution for a relatively small number of measurements of the objective function(Maryak and Spall, 2005).

The findings of a comparison of the very-fast-simulated-annealing (VFSA), finite-difference-gradient (FDG), and SPSA algorithms revealed that a global solution could not be found. On the other hand, SPSA was rather effective in finding a solution that was close to the ideal one (Bouzarkouna et al., 2013).

When computing net present value (NPV) in the presence of geological uncertainty, SPSA was taken into consideration (Luchian et al., 2015).

In the original plan, discrete SPSA, GA, and the finite-difference approach were all included (FD). There was evidence of higher robustness in both DSPSA and GA (Nabaei et al., 2018).

An optimization framework that improves placement of horizontal wells in unconventional reservoirs makes use of SPSA, CMA-ES, and GA. This framework was developed (Ma et al., 2015).

2.1.2 Derivative-based Optimization Methods

Since the 1950s, there has been a significant advancement in the derivative-based approaches. These methods look for the best possible solution by using gradients of the functions being considered. It is a generic method for smooth functions, which means that all of the functions are assumed to be smooth and differentiable. In other words, the technique is designed to work with smooth functions(Mahmood and Al-Fatlawi, 2021).

It is expected that wells will only inject or generate a very low flow rate; as a result, these wells will not have any impact on the overall computation over the lifetime of the reservoir. The adjoint method is used in the computation of the NPV Gradients. After that, these gradients are implemented (Zandvliet et al., 2008).

It is expected that wells will only inject or generate an extremely low flow rate; as a result, these wells will not have any impact on the overall computation over the lifetime of the reservoir. The adjoint method is used in the computation of the NPV Gradients. After that, these gradients are used to optimize the directions in which the wells are shifted in order to get the highest possible NPV(Zandvliet et al., 2008).

The authors proposed an approximation to the native WPO problem that could be carried out in a continuous manner. In this approximation, the calculation of the gradient could be carried out on the approximate problem, and gradient-based algorithms could be used to determine optimal locations in a time-efficient manner. The practical usefulness of this technique was proved using synthetic waterflood optimization issues(Sarma and Chen, 2008).

2.1.3. Mixed-Integer-Programming (MIP)

MIP might be classed as a kind of linear optimization in which the best solution contains integer values for some of the decision variables. In this form of optimization, the minimum information principle (MIP) is used(Mahmood and Al-Fatlawi, 2021).

Optimization of well placement is achieved by the use of a bound and branch MIP in conjunction with the model of the reservoir. However, this strategy can only be used when dealing with linear issues (because of its dependency on superposition)(Rosenwald and Green, 1974).

2.1.4. Simplex method

The simplex technique is regarded as one of the most resourceful and valuable algorithms, and it is still the predominant approach that is used on computers to solve optimization issues (Mahmood and Al-Fatlawi, 2021).

a generic well-placement structure was developed by using the simplex method to cut down on the number of individual wells that were needed to fulfill the preset requirements. The use of this method is limited to gas reservoirs (Mahmood and Al-Fatlawi, 2021),(Siemek and Stopa, 2006).

2.2. Non-Conventional Methods (Metaheuristic algorithms)

When there are several possible solutions to an optimization issue, the use of metaheuristic algorithms such as GA, PSO, DE, and other methods is recommended.

2.2.1. Genetic-Algorithm (GA)

The Genetic Algorithm, sometimes known as GA, is a population-based stochastic algorithm that was one of the first to be suggested in the history of computing. Selection, crossover, and mutation are the primary operators in GA, just as they are in other evolutionary algorithms (EAs)(Mirjalili, 2019).

The mathematical foundation of GA was first published by Jon Holand in the year 1975. The first step in the execution of GA is the initialization of the chromosomes, also known as the population(Al-Juboori et al., 2020). Following this step, a new group of chromosomes is produced that is determined by the fitness value. The process of crossover, mutation, and recombination is carried out in a continuous manner once the GA technique has been initiated in a random manner(Nabaei et al., 2018),(Al-Mudhafar et al., 2010).

An oil reservoir that is undergoing water injection and gas injection will have hybrid GA carried out so that the position of wells may be adjusted. This can be done in both vertical and horizontal wells. Integration of HGA with experimental design (ED) was carried out(Badru and Kabir, 2003).

In addition to the well-known operators of GA, such as crossover and mutation, a novel operator referred to as the "similarity operator" was also presented. This strategy produced methodical advancements toward the solution while further keeping the exploitation and exploratory characteristics of GA(Hamida et al., 2017).

The use of GA in combination with pseudohistory matching yields a more assured result while also cutting down on the amount of time needed for optimization. However, due of the many simulation runs that are required, this method can only be used for a very little reservoir(Lyons and Nasrabadi, 2013).

2.2.2. Particle-Swarm-Optimization Algorithm (PSO)

The intelligent collective behavior of certain animals, such as flocks of birds or schools of fish, served as inspiration for the development of a population-based stochastic optimization technique known as particle swarm optimization (PSO). Since it was first introduced in 1995, it has seen a great deal of development since then. As researchers gained more knowledge about the method, they derived new versions of it with the goal of meeting a variety of requirements, developed new applications in a wide variety of fields, published theoretical studies of the effects of the various parameters, and proposed a large number of different variants of the algorithm(Wang et al., 2018).

A novel method known as well-pattern-optimization (WPO) was used, which 11astern11ped a few of the problems by optimizing the parameters after taking into mind recurring well patterns. In addition to that, a process known as meta-optimization was carried out, which included optimizing the PSO parameters at various stages of the optimization runs. The findings demonstrated that the outcomes obtained by meta-optimization were superior to those obtained by PSO with the default settings (Onwunalu et al., 2010).

Within the scope of this research, a comparison was made between PSO and GA with the goal of optimizing the well site and type. Several scenarios, including vertical, dual lateral, and deviated wells, were taken into consideration. According to the findings, PSO was superior than GA in every instance (Onwunalu et al.,2010).

The PSO algorithm was built using components picked at random. This indicates that the particle is only related to a select number of the other particles in the swarm, and not to all of the particles. As a consequence, the particle exhibits improved behavior on a global scale(Foroud et al.,2018).

Niche-PSO (NPSO) This technique does not impose any continuity requirements on the functions being evaluated. This approach was highly effective at handling a large number of variables that have several dimensions. According to the findings, NPSO performed much better than conventional PSO(Mahmood and Al-Fatlawi, 2022).

2.2.3. Covariance-Matrix-Adaptation-Evolution-Strategy (CMA-ES)

CMA-ES is one of the most effective strategies (algorithms) for the process of evolution, which is supported by the biological principles behind evolution. Techniques that are gradient-free and stochastic and are used for solving optimization issues involving nonlinear, nonconvex optimization problems are referred to as evolution strategy approaches(Mahmood and Al-Fatlawi, 2021).

In order to integrate CMA-ES with meta-models, the development of meta-models that are partly segregated was put into effect. As a result of this, many different meta-models were generated for each well or group of wells, which resulted in more accurate modeling. According to the authors, the methodology was better suited for use in large-scale fields(Bouzarkouna et al., 2011).

Within the scope of this work, the determination of optimum well sites and trajectories for multi-lateral wells based on CMA-ES was taken into consideration. To further improve the effectiveness of this method, rejection with adaptive- penalization and a metamodel planting were used in CMA-ES. This method was more successful than the GA(Bouzarkouna et al., 2012).

2.2.4. Differential-Evolution (DE)

Storn and Price (1997) were the ones who first offered the idea of a global optimization method (1997). DE makes use of a number of different applicant solutions. A combination of the current placements of existing factors is used to determine where new factors should be placed in the search area. To elaborate, an intermediate factor is produced when two factors, which are chosen at random from the pool of current inhabitants, are combined. After then, this transient factor is mixed with a target factor that has already been decided upon. If the new component results in a lower value for the objective function, then it will be considered for inclusion in the generation that comes after this one(Foroud et al., 2018).

Using the DE algorithm and the regional average reservoir pressure as a constraint, a novel method has been developed that is based on maximizing NPV while at the same time reducing VRR as an extra target. This methodology was developed recently(Al-Ismael et al., 2018).

Use WPO for offshore reservoirs by using the minimal value of the Theil index (objective-function). In order to achieve optimum placement, we made advantage of constraints like the minimum inter-well distance and the infilling scope(Chen et al., 2018).

3. Well Placement Constraints

Through the imposition of restrictions on the process, constraints contribute to the determination of a workable design and area for the purpose of the optimization problem's solution. The optimization methodology might potentially arrive at a solution; however, if the constraints are not satisfied, optimization could result in solutions that are not practicable. The use of constraints helps to avoid the optimization issue from having a solution that is too simplistic(Mahmood and Al-Fatlawi, 2021).

For the first population, a number of restrictions and requirements have been outlined. Some of these limitations were imposed to guarantee that the wells that are produced can be drilled, while others were done so to prevent the development of solutions that are known to have poor performance, which may be the result of the solutions' potential violation of standard practices in petroleum engineering. When we consider that we are in charge of the process of initialization, it should not be difficult to apply the limitations to the initial population. In order to solve the infill well placement issue, the following limitations have been defined(Agbauduta, 2014):

- The oil saturation (Soil) at the proposed site for infill well placement has to be larger than or equal to the total of the residual oil saturation (Sor) and 10 percent. This requirement must be met in order for the infill well placement to proceed. This indicates that any area for the installation of an infill well must have an oil saturation level that is greater than the residual oil saturation level and has a margin of at least ten percent. This is done to ensure that the proposed area is capable of producing a sufficient quantity of oil and that it is viable for use. The search space is narrowed down to include just those sites that fulfill all of the requirements mentioned in this restriction. The primary goal here is to stay away from areas that have a low saturation of oil in the ground. This requirement may be expressed using mathematics as follows: Soil (Sor + 10%).
- It is necessary for the suggested site to have an average pressure that is higher than the minimum required pressure for the reservoir. This constraint is in place to ensure that the average reservoir pressure of the grid block selected for infill well placement has sufficient pressure to produce the oil, which means that it must be higher than the threshold pressure of the reservoir. In other words, this constraint ensures that the oil can be produced.
- This reservoir model has two different kinds of borders: a no-flow boundary, often known as a fault, and an aquifer. Both of these types of limits prevent water from flowing through the reservoir. Every time there is flow, it moves in a direction that is perpendicular to the border where there is no flow. The well placement constraint for the boundary condition is set up in such a way that wells are not allowed to be placed in close proximity to faults or no-flow boundaries, and they are also not allowed to be placed in close proximity to the aquifer in order to prevent water coning and high water-cut. All of the prospective sites that are located in close proximity to faults, aquifers, or oil-water contacts (OWC) are deleted from the original population and are no longer considered to be possible places for infill well placement.
- There are 2660 blocks in the model of the reservoir, however only 1761 of those blocks are active. In the active blocks of the reservoir mode is the only spot where any possible infill well may be put and finished.

4. Simplex Non-Linear

The Simplex Nonlinear Optimizer is an enhanced version of the Simplex Optimizer that also permits the imposition of non-linear restrictions on model responses and control variables (Nelder and Mead, 1965).

Fig.1 displays in a graphical format the amount of computing effort required by various sorts of restrictions. Although linear and limits calculations are very cheap to do, nonlinear simulation-based calculations may run up a hefty bill (Mahmood and Al-Fatlawi, 2021).

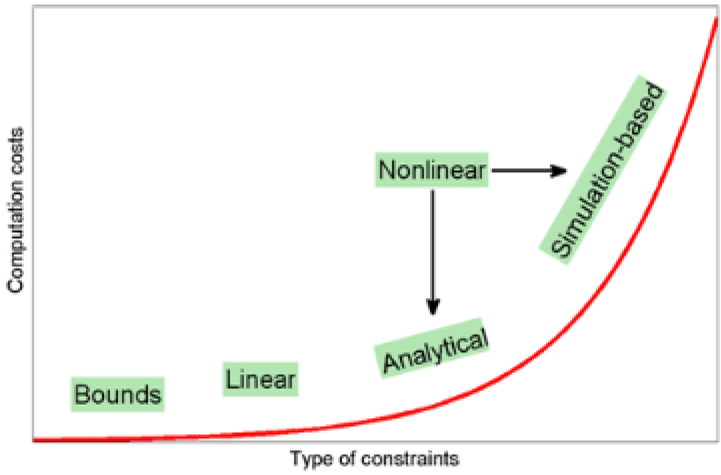
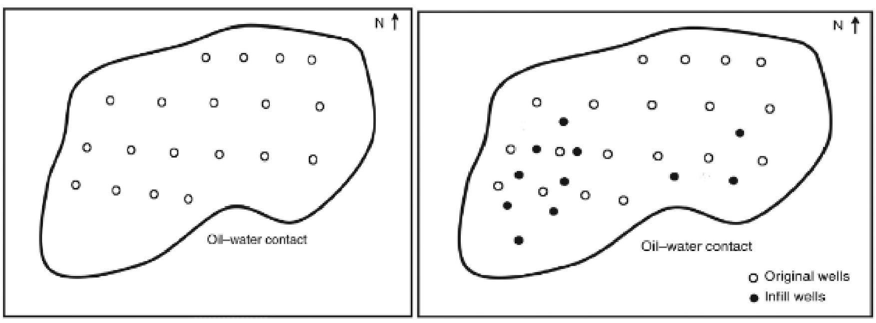


Fig.1. The various types of limitations and the associated costs

The nonlinear issues that are being handled by the implemented algorithm in the simplex non-linear optimization approach are being converted using a method that is based on a sequential lexicographic comparison. This transformation is taking place while the nonlinear problems are being solved. The sequential lexicographic comparison will start by addressing the linear constraints, then it will move on to the low-cost non-linear constraints, then it will move on to the costly non-linear constraints, and finally it will address the objective function. This process will be repeated until all of the constraints have been taken into account. As a consequence of this, the objective function is only computed in those areas where it is feasible to do so, and estimates for the expensive constraints are only produced in those sites where they can be met in their whole(Mahmood and Al-Fatlawi, 2021).

5. Infill Drilling

Infill wells are a way of enhancing the efficiency of sweeping by the addition of new wells in the reservoir that reduces average well-spacing. Moreover, connectivity between injectors and producers will be improved, and overall better reservoir economics will be established. These infill wells are anticipated to reach portions of the formation that have high oil saturation. However, drilling such a large number of wells is associated with the complexity of selecting the optimum location for each well that accelerates the field's recovery (Al-Fatlawi et al., 2017). Because reservoir characterization is being made to be more in-depth, which will result in more aggressive models being simulated, it is likely that some areas of the formation will not be drained correctly by the initial phase of development. The modern practice of infill drilling focuses on specific places rather than adopting a regular pattern of drilling, as seen in Fig.2 below.



(a) (b)

Fig.2. Infill drilling scenario (a) before infill drilling; (b) after infill drilling.

6. Conclusions

The most popular algorithms for tackling WPO problems are GA and PSO, along with some of their modifications. Stochastic methods are sensitive to parameter tuning, but in most cases, they have reached higher NPV, and gradient-based performance continues to be better in large fields while stochastic algorithms are performing well in small fields.

Based on the survey done in this paper, no single unique optimization technique can be recommended for all cases of infill drilling wells projects because the wide range of diversity of decision variables, the heterogeneity of the reservoirs and other limitations logistics conditions. Consequently, the most suitable optimization technique for choosing the right themes and well spacing in the reservoir model will be that technique which leads to maximize the maximizing the primary objective function for developing which it is net present value (NPV).

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