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An efficient geometry-based optimization approach for well placement in oil fields

Zachary Hamida[a], Fouad Azizi[b], George Saad[c,*]

[a] Graduate Program in Computational Science, American University of Beirut, Beirut, Lebanon
[b] Department of Chemical and Petroleum Engineering, American University of Beirut, Beirut, Lebanon
[c] Department of Civil and Environmental Engineering, American University of Beirut, Beirut, Lebanon

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ABSTRACT

This study aims at introducing a problem-specific modified Genetic Algorithm (GA) approach for optimal well placement in oil fields. The evolution method used in this algorithm includes a novel genetic operator named "Similarity Operator" alongside the standard operators (i.e. Mutation and Crossover). The role of the proposed operator is to find promising solutions that share similar features with the current elite solution in the population. For the well placement problem in oil fields, these features include the new well location with respect to pre-located wells and the porosity value at the proposed location. The presented approach highlights the importance of the interaction between the nominated location and the pre-located wells in the reservoir. In addition, it enables systematic improvements on the solution while preserving the exploration and exploitation properties of the stochastic search algorithm. The robustness of Genetic Similarity Algorithm (GSA) is assessed on both the PUNQ-S3 and the Brugge field data sets.

1. Introduction

Throughout the different stages of oil field development and planning, decisions have to be made continuously to maintain the sustainability of the project's dynamic nature. Several reservoir engineering problems were addressed in the literature, and a big proportion was devoted for the well placement problem. Prioritizing the well placement problem is due to the high costs following decisions related to drilling and adding new wells. This problem is commonly formulated as an integer programing problem, whereby the optimization variables are the indices of the reservoir model cells.

Different optimization algorithms were suggested to solve this problem (Handels et al., 2007; Sarma and Chen, 2008; Bittencourt and Horne, 1997; Güyagüler et al., 2002). The efficiency of these algorithms was measured by solution robustness, convergence rate and the total computational cost of the process. Handels et al. (2007) and Sarma and Chen (2008) applied gradient-based search with variations to account for the high heterogeneity of the search space. The gradient-based search algorithms have a systematic convergence due to having a search direction. However, these algorithms may suffer from limitations and drawbacks that weaken their reliability; namely, difficult implementation, high computational cost (i.e. calculating search direction), inability to explore the search space efficiently, and a tendency to converge to the first sub-optimal solution. For the aforementioned reasons, derivative-free algorithms present themselves as a more reliable option in solving the problem. Derivative-free search algorithms can be mainly categorized in two groups: local search methods which apply local adjustments on the solution candidates (i.e. simplex method) and global search methods (i.e. population-based algorithms) (Rios and Sahinidis, 2013). Different population-based algorithms were applied in the literature to solve the problem of well placement in oil fields (Güyagüler et al., 2002; Montes et al., 2001; Onwunalu and Durlofsky, 2009; Afsharia et al., 2011). Montes et al. (2001) applied Genetic Algorithm (GA) search to solve for well placement in oil fields and assessed the impact of different parameters on the algorithm performance (i.e. mutation to cross over ratio, starting point...etc.). Onwunalu and Durlofsky (2009) applied a Particle Swarm Optimization (PSO) algorithm to search for optimal well location and type (production or injection). Afsharia et al. (2011) assessed the performance of an Improved Harmony Search (IHS) algorithm Mahdavi et al. (2007), which has a better local search performance than the standard HS, in solving the well placement problem. As the aforementioned algorithms have a general context that doesnot account for computationally expensive objective function, variations to these algorithms were introduced aiming at improving the convergence rate at a minimum computational cost. Bittencourt and Horne (1997)

* Corresponding author.
E-mail address: george.saad@aub.edu.lb (G. Saad).

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used a hybrid algorithm of GA and polytope method to solve for optimal well placement. da Cruz et al. (1999) introduced the Quality Map approach to present a different way of evaluating well locations while limiting the use of the reservoir simulator. Güyagüler et al. (2002) used Hybrid Genetic Algorithm (HGA) (Genetic Algorithm +simplex method+surrogate model) to search for optimal location and flow rates for the added wells.

Although population-based algorithms have had a superior performance in terms of usability and convergence rate, the search-space of the well allocation problem still imposes difficulties that may hinder the efficiency of these algorithms. For example, population-based algorithms might evaluate and propose locations of a low quality for wells, such as locations adjacent to pre-located wells or locations not within the active cells of the reservoir model. This is due to the stochasticity of the operators used in nominating locations for wells. Also, early convergence or premature convergence of a population may contribute to increasing the number of ineffective simulation runs. These factors combined consume a significant portion of the total computational cost required to find an optimal well location.

Customization techniques for these algorithms were applied to make them adapt to the search-space of the problem (Li and Jafarpour, 2012; Awotunde and Naranjo, 2014). This was mainly achieved through the objective function formulation or applying constraints on the search space. One of the commonly used approaches in formulating the objective function is the penalty and reward approach. This approach suggests adding a penalty parameter to the objective function to account for the problem non-practical solutions. Although this type of formulation can aid the search algorithm in identifying the less plausible solutions, it doesnot contribute in finding new good solutions.

In this study, a new genetic operator named “Similarity Operator” is proposed to efficiently solve the well placement problem in oil fields. The operator will function alongside the standard genetic algorithm (GA) operators (i.e. Crossover and Mutation) and aims at searching for solutions that share similar features with the current elite solution in the population. This new framework will be referred to as Genetic Similarity Algorithm (GSA). The addition of this new operator will provide potentially good solutions while preserving the exploration and exploitations properties of the standard operators.

The use of Genetic Algorithm was mainly intended to demonstrate the significant performance improvement that can be obtained in contrast with a standard implementation of the algorithm. Since population-based algorithms have a general context and their performance is highly dependent on the parameter settings as well as the problem description, every search algorithm may have an edge in solving for a certain problem (Deb and Padhye, 2014; Padhye et al., 2013). Therefore, the customizations introduced in the GSA framework account for the broad generality of the previously applied approaches by incorporating information about the search-space of the problem when searching for new solutions.

2. Genetic Algorithm

Introduced by Holland (1975), Genetic Algorithm (GA) is a stochastic search algorithm motivated by the principle of evolution. GA has an efficient performance in problems with high number of input variables as well as high number of local optima. The algorithm explores the search space through a population (generation) of solutions (individuals), and these solutions evolve based on a fitness value obtained from the objective function. The fittest individuals within a generation will undergo genetic operators (i.e. mutation and crossover) to generate a new generation replacing the previous one. Fig. 1 illustrates the different stages in GA search for solutions. Since this study is suggesting a change in the GA framework, it is convenient to tackle the role of each stage and operator within GA. The following is a brief description for the GA main stages.

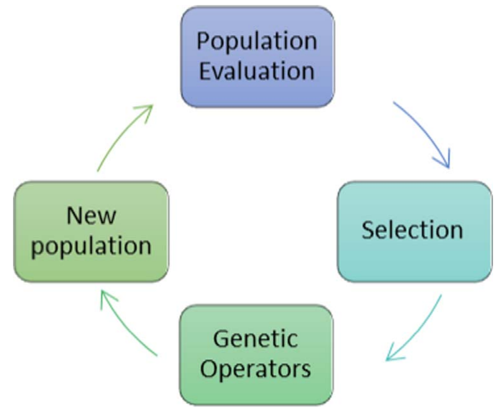

Fig. 1. Genetic Algorithm Structure.

2.1. Selection

After evaluating all the individuals in a generation, the algorithm will rank these individuals based on their fitness value. The ranking determines the individual probability of survival in the selection process. Different selection techniques were developed in the literature (i.e. roulette wheel, tournament, uniform …etc.) (Goldberg and Deb, 2013), however, the choice of a selection technique is highly dependent on the variation in the fitness function values.

2.2. Genetic Operators

Genetic operators perform operations over individuals that survive the selection stage. Each genetic operator contributes to the next generation with a predefined proportion of individuals. The following are some of the commonly used genetic operators:

- ***Elitism***: The Elite operator role is to move the best individuals in the population to the next generation without changes. This operator helps preserving good solutions in the population; however, it may also contribute to the occurrence of early convergence in the population due to replicating the same individual(s) multiple times in the next generations.
- ***Mutation***: The goal of mutation is to reassure the diversity in the population. The operator alters values within a single individual at different locations in the encoded string. Different instances of the mutation operators were developed (i.e. Gaussian, uniform and bit flip), accounting for different types of problems. Mainly the choice of the mutation operator is dependent on the search space properties (i.e. integer or continuous).
- ***Crossover***: The crossover combines and merges the selected individuals to generate new individuals. Similar to the Mutation operator, many instances of the Crossover operator (i.e. single point, two point, arithmetic …etc.) were developed and used depending on the problem being solved.

3. Genetic Similarity Algorithm (GSA)

The proposed search algorithm presented in Fig. 2a and b is based on the aforementioned GA with an additional operator named “Similarity Operator” to help explore the search space more efficiently. The Similarity Operator aims at finding promising solutions by exploring the search space in a systematic manner. The solutions proposed by the operator share certain search-space features with the current elite solution in the population. The techniques used in building the operator will be described in details in the following sections.

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