Hybrid Optimization Using Convolutional Neural Network for Well Placement in Oil Fields

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Abstract

In oil field development and planning, making decisions to allocate new wells in an oil reservoir is a challenging problem. The challenge arises from the fact that a production forecast is needed to evaluate the efficiency of the selected location. This forecast has a high computational demand as it depends on simulating the fluid flow in the model. Different parameters acquired from the simulation run output can be used in formulating the cost function of the problem. However, the production quantities of oil and water are commonly associated with the project economical profits and costs respectively. Thus, the ultimate consideration when allocating additional wells is to maximize the oil produced while minimizing the total water injected or produced from all wells.

At the computer model level, the wells are only feasible to be allocated on the grid-blocks (mesh) of the reservoir geological model. Therefore, the well placement problem is commonly formulated as an integer programming problem. Different optimization techniques were applied in the literature to account for well placement in oil fields. Gradient-based methods were used with variations. These variations' main goal is to avoid converging to local optimal solutions. Handels et al. (2007) [1] and Sarma et al. (2008) [2] proposed improvements on the gradient search direction to increase the exploration capabilities of the algorithm. Although, gradient methods are systematic in converging to a solution, still they suffer from multiple drawbacks. The most relevant drawbacks are: the high computational cost of calculating the gradient at each iteration, the high sensitivity to the starting point and the poor performance in a search space with multi local optimal solutions, which could have the algorithm to lock-in a local optimum. On the other hand, population-based search algorithms were employed to overcome the complexity of gradient methods [3, 4, 5]. However, population-based search algorithms may require a high number of iterations to guarantee converging to a reliable solution. Surrogate-assisted optimization (or hybrid optimization) methods were proposed [6, 7, 8] to relax this

requirement. A hybrid optimization framework attempts to relax the dependency on the reservoir simulator through building and using a surrogate model to estimate the reservoir simulator response. The surrogate model is constructed based on the input-output combinations obtained from the reservoir simulation runs.

A variety of surrogate-assisted optimization techniques were addressed in the literature. Da Cruz et al. (1999) [9] introduced the Quality Map approach to replace the reservoir simulator with a distance-based formula after a finite number of simulation runs. Guyaguler et al. (2002) [6] and Badru et al. (2003) [10] coupled Genetic Algorithm (GA) with Artificial Neural Networks (ANN) and then with Kriging along with a local search algorithm to search for optimal well locations. Salam et al. (2015) [7] used Latin Hypercube sampling to initialize a combination of GA and ANN for optimal well allocation.

The performance of a surrogate-assisted optimization algorithm is directly associated with the surrogate model used [6]. Consequently, the choice and design of a surrogate model are based on the problem complexity. For example, finding an optimal location for a single well requires a simpler surrogate model than finding optimal locations for multiple wells. This is due to the increase of the problem nonlinearity as the number of optimization variables increases.

In this study, a regression Convolutional Neural Network (CNN) is proposed for replicating the reservoir simulator response within a hybrid GA-CNN optimization framework. This framework will be employed in solving the well placement problem in oil fields. CNNs have had a major success in object detection and computer vision applications compared to traditional computer vision algorithms [11, 12]. The use of CNN in this study will assist the optimization algorithm by identifying patterns of well locations associated with high oil 3 production. This will allow a better convergence rate (less computational cost) to be achieved especially when the number of well locations to be optimized is relatively high. Furthermore, a better scalability for the surrogate model is expected, since the CNN model is operating on fixed-size input (images). The GA-CNN optimization framework will be benchmarked against commonly used hybrid frameworks (i.e. GA-ANN) in the literature.