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Using the Producer Well Economic Indicator to Improve a Metaheuristic for Well Placement Optimization in Petroleum Fields

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Abstract. Optimizing the production strategies in oil fields is a challenging problem. The underlying optimization problem usually has a large search space coupled with a high solution evaluation cost, given that it involves computationally expensive simulations in oil reservoir simulation software. At the same time, efficiently addressing the problem is highly desirable as it is directly related to the infrastructure's cost and the profits over the field's life cycle. In this paper, we propose using the Producer Well Economic Indicator (PWEI) of producer wells to improve Iterative Discrete Latin Hypercube Sampling (IDLHC), a heuristic for production optimization. Although IDLHC has been successfully applied to solve problems with a large number of decision variables and compared favorably to other heuristics from the literature, the method does not consider information from the domain of the problem in its search process. Therefore, we analyze using the PWEI, an individual well metric related to productivity, to help guide the search process. Our approach was able to both accelerate the early stages of the search and improve the average objective function value at the end of the optimization process, as evidenced by extensive computational experiments.

Keywords: Metaheuristic, production optimization, net present value, well economic index, combinatorial optimization

1 Introduction

The Prodution Strategy Optimization Problem (PSOP) in petroleum fields consists of determining the production strategy that maximizes a given performance metric, such as the net present value (NPV). The problem is of great practical interest due to the magnitude of costs related to the production infrastructure. However, solving the PSOP efficiently is a challenge due to the combination of a large search space and a high computational cost to evaluate each candidate production strategy. The high solution evaluation cost is related to the necessity of running computational simulations using oil reservoir simulation software. Such simulators estimate the behavior of a given production strategy over the concession period of the field. The process can take several hours, depending on the level of detail in the oil field model.

In other words, the PSOP consists of determining the production infrastructure of an oil field that maximizes a given performance measure. According to Gaspar et al. [1], the variables used to determine the production strategy can be classified into project (G1), control (G2) and revitalization (G3) variables. The variables from the first group were the focus of this work. They define the production infrastructure before field development begins, determining the number, type and positions of wells. The objective function considered in this work is the maximization of the NPV, which is the net cash flow over the concession period of the oil field. The NPV of a given production strategy is calculated from data obtained through the simulation of the respective strategy in numerical reservoir simulation software. As mentioned previously, this step has a high computational cost and, therefore, is one of the main challenges in efficiently solving the PSOP. In this scenario, metaheuristics are a promising class of algorithms. However, the use of standard metaheuristics to solve real PSOP instances is usually impractical due

to prohibitive computational times.

More formally, let V be a set of decision variables that determine a production strategy. Variables are either numerical or categorical, and it is assumed that they are discrete. Each variable $v_i \in V, i = 1, \ldots, n$ has a domain K_{v_i} that contains all possible values that v_i can take. The PSOP consists of determining the set of values of the variables v_i that maximizes the NPV of the respective production strategy. Finally, the NPV was calculated according to the definitions in Gaspar et al. [1].

The PSOP has been addressed in the literature through a variety of methods, such as genetic algorithms [2–4], differential evolution [5–7] particle swarm optimization [8–10], and estimation of distribution algorithms [11–13], just to name a few. Frequently, the PSOP is addressed as a black-box optimization problem, i.e. no information about the domain of the problem is considered during the optimization process. However, some methods do use information such as quality maps [4, 14], well spacing constraints [10], and indicators such as the threshold value of productivity potential [15] and the producer well economic indicator (PWEI) [1].

In this work, we extend a method from the literature to use information about the domain of the problem. More precisely, we modify the Iterative Discrete Latin Hypercube (IDLHC) [16] heuristic from the literature and extend it to consider the PWEI. IDLHC is an iterative, population-based heuristic search method. This means that the method improves a set of solutions, i.e. production strategies, through successive iterations. Such a set of solutions, which is generated at each iteration, is called a *population*. Furthermore, IDLHC uses a probabilistic model to sample the population and guide the optimization process. Evaluating a population consists of simulating each production strategy and is, therefore, a computationally expensive process. At the end of each iteration, the probabilistic model is adjusted based on the current population to guide the search to promising regions of the search space. We chose IDLHC motivated mainly by its flexibility, good results when tackling problems with a large number of variables, and favorable comparison with other optimization methods from the literature [16–18].

2 Methodology

Our research focused on adapting the IDLHC to consider information from the reservoir engineering context in its optimization process. In the new version of IDLHC that we developed, in addition to the NPV of the production strategy, the method also checks the PWEI of producer wells and uses this data to help guide the optimization process.

The PWEI is an indicator related to the individual performance of producer wells that considers the sum of revenues from the sale of oil and gas, minus the production costs and investment required for the respective producing well. Formally, the PWEI is calculated as follows:

$$PWEI = \sum_{t=1}^{T} \frac{R_O + R_G - C_O - C_G - C_W - I}{(1+r)^t}, \tag{1}$$

where R_O is the revenue from the sale of oil, R_G is the revenue from the sale of gas, C_O is the cost related to oil production, C_G is the cost related to gas production, C_W is the cost related to water production, I is the well investment, and r is a certain minimum attractiveness rate [1]. The calculation is made considering each time instant $t = 1, \ldots, T$.

Producers with high PWEI will be more likely to be selected in future production strategies compared to producers with low PWEI. In the standard version of IDLHC, the probability of selecting a well x for a given production strategy is determined by the frequency of x in the subset with the best production strategies that the method found in the previous iteration. More precisely, the probability P_x^{t+1} of a producer well x being selected in iteration $t+1$ is

$$P_x^{t+1} = n_x^t / m^t, \tag{2}$$

where n_x^t is the number of production strategies in iteration t in which well x is present, and m^t is the size of the subset containing the best production strategies generated during iteration t. On the other hand, the variant developed in this work considers a weighted sum of eq. (2) and the producers' average PWEI when assigning probabilities to each well. More precisely, the probability P_x^{t+1} is determined by the following weighted sum:

$$P_x^{t+1} = \frac{Z_1 \cdot (n_x^t / m^t) + Z_2 \cdot w_x^t}{Z_1 + Z_2}, \tag{3}$$

where Z_1 and Z_2 are constant weights, and w_x^t is the average PWEI of the producing well x in iteration t normalized to the interval $[0, 1]$. Note that the method is equivalent to the standard IDLHC when $Z_2 = 0$.

3 Computational experiments

The weights Z_1 and Z_2 can be seen as parameters that need to be calibrated for the method to reach its full potential. Therefore, extensive computational experiments were carried out to calibrate the weights as well as to evaluate the developed algorithm. For the computational experiments, the UNISIM-II-D [19] benchmark was used.

UNISIM-II-D combines data from pre-salt reservoirs and the well-known Ghawar Field, which has characteristics similar to those of pre-salt reservoirs. The model contains approximately 95000 cells with approximately 41000 active blocks measuring $100 \times 100 \times 8\,\mathrm{m}^3$ each. The optimization problem domain contains 127 binary variables that define the number and location of wells. The search space contains a total of 2^{127} possible solutions. Fig. 1 presents a visual representation of the UNISIM-II-D reservoir.

Since the method is stochastic, five independent samples were taken in each case and the results presented are, therefore, the average of the five samples. In each sample, the algorithm was limited to a total of 3000 simulations. Upon reaching this number, the execution was terminated and the production strategy with the highest NPV obtained during the search process was returned.

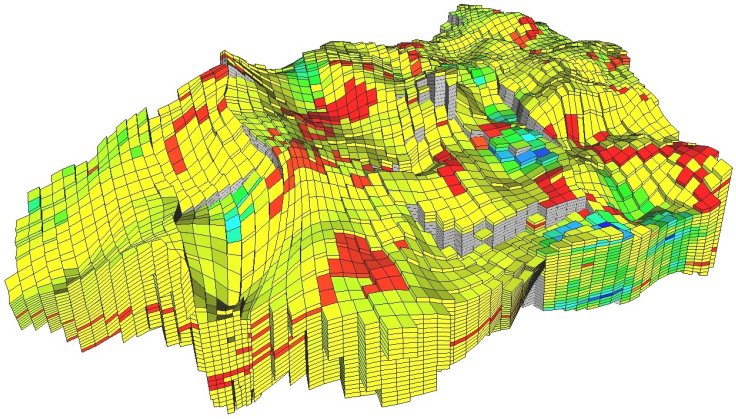


Figure 1. Reservoir in the UNISIM-II-D benchmark.

We divided the experiments into three sets. In the first set, greater weights were assigned to the frequency of the wells, *i.e.* $Z_1 > Z_2$. In this case, we defined $Z_2 = 1$ and $Z_1 \in \{2, 3, 4, 5, 10\}$. When it comes to the average NPV obtained at the end of the method execution, all values produced improvements compared to the standard IDLHC, with $Z_1 = 5$ and $Z_1 = 10$ producing the best results (improvement of around 2.5% on average).

Next, we analyzed the evolution of NPV throughout the optimization process. A comparison between the different weights and the standard IDLHC is shown in Fig. 2, where the x axis refers to the progress of the process (as the number of simulations run grows), while the y axis contains the NPV value of the best solution obtained so far during the search. Each curve represents the average of the five runs. Furthermore, the legend identifies the weights used in each case, with "IDHLC_wAwB" indicating that $Z_1 = A$ and $Z_2 = B$. The case identified only as "IDLHC" refers to the standard IDLHC approach that does not use the PWEI. In addition to the improvement in the NPV obtained at the end of the optimization process, one can note that, for all weights evaluated, the methodology developed in this work also generated a slight improvement in the initial stage of the search, approximately in the range between 200 and 700 simulations performed.

In the second set of experiments, we evaluated weight assignments with $Z_2 > Z_1$. One can observe that, despite resulting in a decrease in the final NPV (between 2.2% and 3.6%), this approach allowed the method to obtain good solutions more quickly compared to the standard IDLHC. In other words, this approach considerably accelerated the initial stages of the search process and is therefore especially suitable for scenarios where the number of simulations allowed is small. Fig. 3 presents a comparison of the evaluated weights. Note that the gain compared to IDLHC is approximately in the range between 100 and 600 simulations run. After 1000 simulations a significant disadvantage can be noticed.

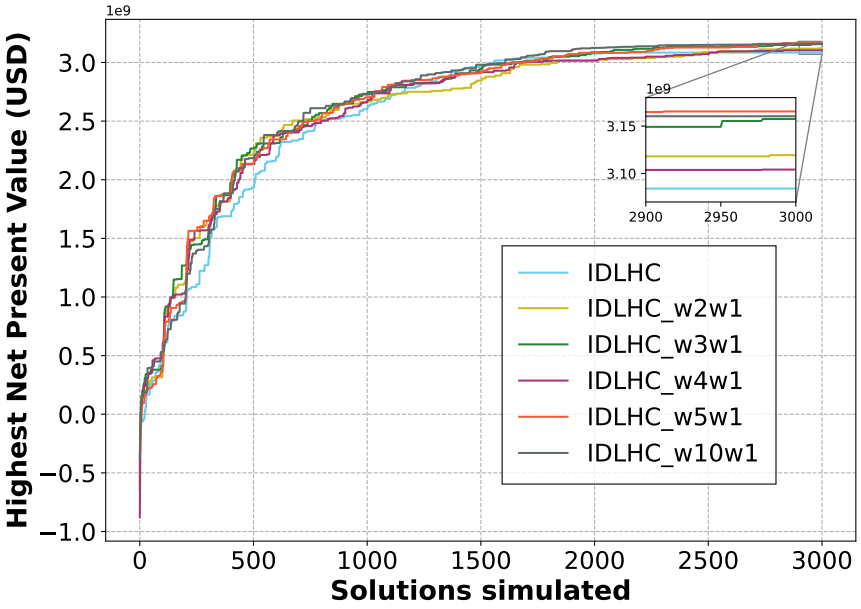


Figure 2. Experiments in which $Z_1 > Z_2$.

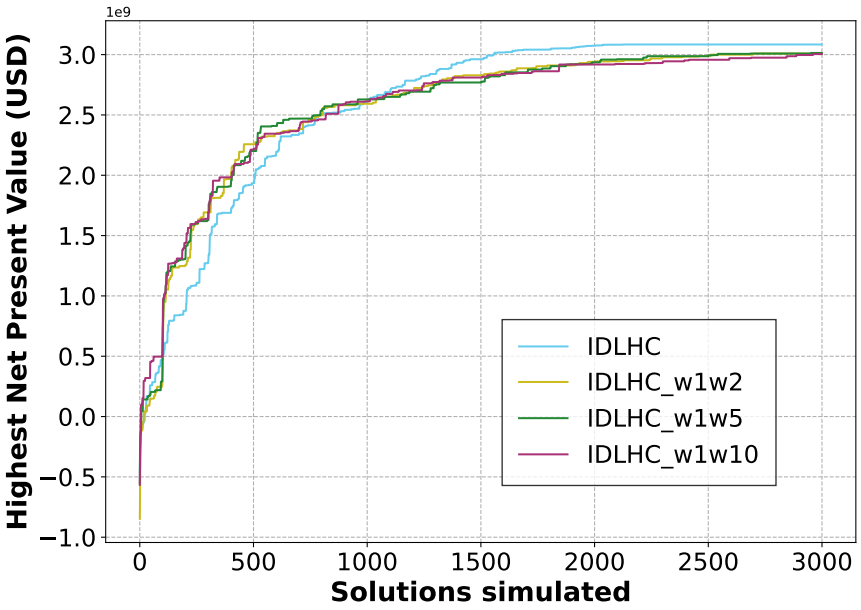


Figure 3. Experiments in which $Z_2 > Z_1$.

Finally, the third set of experiments evaluated the case where $Z_1 = Z_2$. This approach was detrimental to the final NPV, but was able to speed up the start of the search. However, this combination of weights was slightly less effective than the previous approach (in which $Z_2 > Z_1$) with regard to acceleration. The comparison with standard IDLHC is shown in Fig. 4.

Furthermore, we performed an additional experiment in which we aim to combine the strengths of the best approaches found in the previous experiments. In this case, we developed two alternatives that use adaptive weights. In the first one, we start IDLHC with the weights set to $Z_1 = 1$ and $Z_2 = 5$, and change them to $Z_1 = 10$ and $Z_2 = 1$ when the algorithms reaches 700 solution evaluations (7^{th} iteration of the algorithm). The second approach

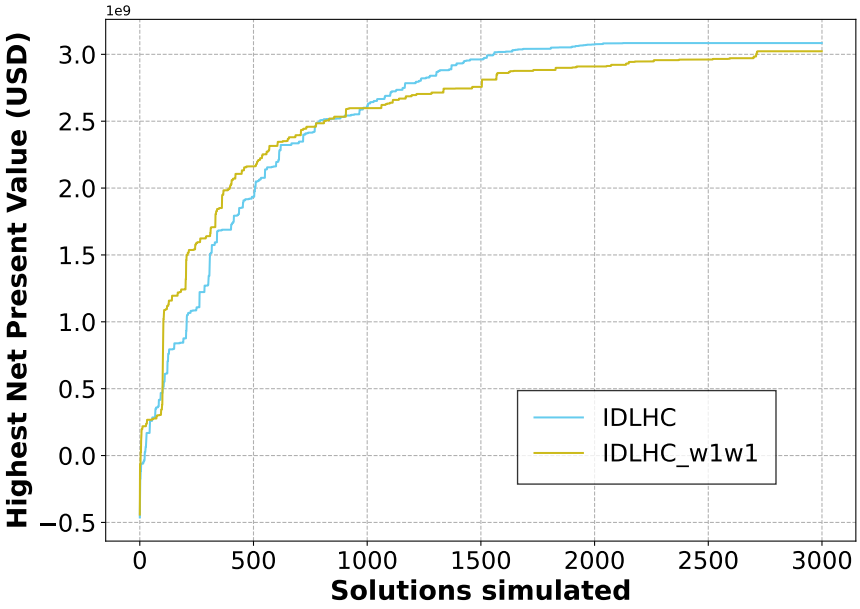


Figure 4. Experiments in which $Z_1 = Z_2$.

is similar, but the weights are changed gradually. More precisely, we start IDLHC with the weights set to $Z_1 = 1$ and $Z_2 = 5$. Once the algorithm reaches 500 solution evaluations (5^{th} iteration), it starts to gradually increase Z_1 and decrease Z_2 until 1500 solution evaluations are performed (15^{th} iteration), the point at which the assignment $Z_1 = 10$ and $Z_2 = 1$ is reached and maintained until the end of the execution. The weight modifications are uniform and performed once per iteration of the algorithm, i.e., Z_1 is uniformly increased from 1 to 10 and Z_2 is uniformly decreased from 5 to 1 through 10 iterations. The results for both approaches are shown in Fig. 5 in which they are named "IDLHC_best" and "IDLHC_best_gradual", respectively. We can see that both improve over the standard IDLHC in early and late stages of the search process, with a slight advantage for the latter method.

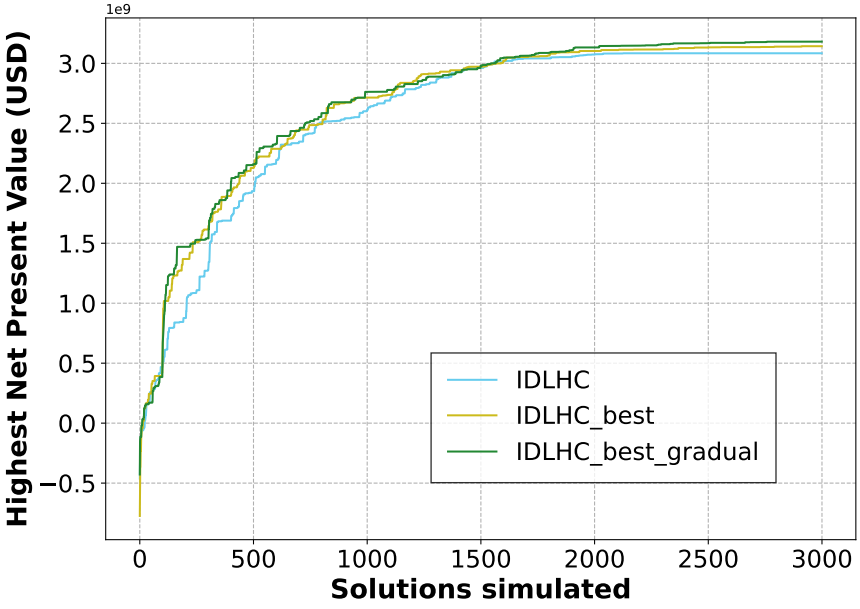


Figure 5. Comparison of the approaches with adaptive weight assignments.

Finally, Table 1 presents the average NPV value obtained at the end of the optimization process for all the experiments. Among all the evaluated cases, the best results were obtained with the adaptive weights that are gradually changed ("IDLHC_best_gradual"). This approach yielded an average improvement of about 3% over the standard IDLHC. The improvement is very significant as it amounts to about 100 million USD. Besides the improvement in the NPV, we also reiterate that our approach accelerates the search process, allowing one to obtain good solutions with fewer simulations.

Table 1. Mean NPV at the end of the optimization process.

Z_1	Z_2	Mean NPV ($\times 10^9$ USD)
1	1	3.02 ± 0.05
2	1	3.12 ± 0.08
3	1	3.15 ± 0.05
4	1	3.10 ± 0.08
5	1	3.16 ± 0.05
10	1	3.16 ± 0.03
1	2	3.01 ± 0.07
1	5	3.01 ± 0.06
1	10	2.98 ± 0.05
IDLHC		3.08 ± 0.07
IDLHC_best		3.14 ± 0.07
IDLHC_best_gradual		3.18 ± 0.03

4 Conclusions

We proposed using the PWEI to aid in guiding the optimization process regarding the PSOP. More precisely, we modified a metaheuristic from the literature, namely IDLHC, to be guided by a weighted sum of the average PWEI and the frequency of wells in good candidate production strategies.

In summary, we were able to use the PWEI to improve IDLHC with regard to the quality of the final solution and to accelerate the search process. In particular, the best results were obtained with an approach with adaptive weights that gradually change during the algorithms's execution. However, several of the evaluated variants yielded better results than the standard IDLHC. Given the high relevance of optimizing production strategies in the industry, the proposed methodology provides a good alternative for obtaining high-quality solutions with a relatively small number of simulations. Furthermore, considering the magnitude of the values involved, adopting the proposed methodology can result in a significant economic gain.

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