Well Placement Optimization Using Firefly Algorithm and Crow Search Algorithm

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Abstract. *Optimization of well placement is one of the main difficult factors in the development process in the oil and gas industry. The well placement optimization is high dimensional, multi-modal and discontinuous. In previous research, conventional and non-conventional optimization techniques have been applied to resolve this problem. However, gradient-free optimization techniques such as genetic algorithm and particle swarm optimization which is considered as the most efficient algorithms in this area suffer from local optima. In this article, two new metaheuristic optimization techniques, namely, crow search algorithm and firefly algorithm are applied to the well placement optimization problem and their applications to maximize the net profit value are studied. To study the performance of the firefly and crow search algorithm, Eclipse and MATLAB environment are used. The proposed techniques are compared to popular established methods for optimizing well placement. Results show that the firefly algorithm is proved to be efficient and effective compared to other established techniques. However, the standard crow search algorithm is not suited to this problem.*

Keywords

1. Introduction

Well placement optimization has been a major issue in the field development process for a while due to its high dimensional, discontinuous and multimodal objective function. For the successful supply and longevity of the operation, placement selection of such well is very important. In recent years, to deal with the increasing global energy demand the correct well placement optimization has been at the center of many studies [1]-[6]. There are several processes of finding out the best possible place for well to ensure uninterrupted oil supply. Still, due to the vast infrastructural work related to such place-

ment, it is very crucial to make sure that the well is going to be in the best available area. In brief, net profit value should be kept under consideration while running the well placement process. In order to maximize net profit value, several works have already been done with different mathematical algorithms. Previous studies have established that algorithms based on gradient and derivatives remain quiet inconsistent and ineffective due to the non-smooth, discontinuous and high dimensional objective function [1, 7]. Some prior research was able to find local optima using gradient-based algorithms [8]. Again, some other well-known techniques such as mixed-integer programming [9], multivariate interpolation algorithms [10], etc. were also used to find the possible best location. However, these methods failed to live up to the expectation and hence researchers put more emphasis on non-classical methods. These methods are inspired by different natural phenomenon and showed more viability in finding global optimum value.

At first, Guyaguler and Horne used GA to optimize well location and injection rate by considering the net present value (NPV) as the objective function [11]. Quality maps are incorporated as nonlinear constraints which helped to determine the correct location for the correct placement of the well [12]. Lyons and Nasrabadi reduced the calculation time by four times by combining pseudo-history matching with genetic algorithms (GA) [13]. Chang, Y. in his research work, showed that NSGA II is an effective and powerful method for solving multiobjective problems [14]. In another study, it is observed that the genetic algorithm is effective and robust for accurately solving the well placement problem [15]. Overall, GA is one of the most popular technique for optimization purposes in well location optimization problems. Generally speaking, GA can find the global optimal value, but the convergence speed is slow. The genetic algorithm-based optimization method was used effectively, but doubt was cast upon issues like absolute convergence and stability [16]. Again, such algorithms have limitations like non-linearity and dis-continuity [17, 18]. Onwunalu used PSO in his research, and has reduced the search space by gradually

moving from an exploration mode to an exploitation mode [19]. But this gradual change may affect the result of different search space. Feng et al. implemented the PSO algorithm proposed by Clerc, which reduced the search process [20, 21]. In the PSO algorithm, the neighborhood topology allows different modes of flight between its particles which provides different searches for swarms in the landscape. The researchers solved the problem of optimizing the well location by utilizing random neighborhood topology with PSO [7, 22]. This solution provides better results and avoids local optimization. But more recent researches are mainly focused on hybrid combinations. In [23], a hybrid of approximation algorithms and linear relaxation with the classical heuristic algorithm was developed in order to gain better results in a more precise time. Moreover, authors in [24], used local search techniques. Another combination named "Baldwin effect" was deployed in [25, 26]. Authors in [27], used hybrid particle swarm differential evolution (HPSDE) to find the optimum solution for well placement problems. From the result, it is clear that HPSDE algorithm outperforms both DE and PSO algorithms. Dossary and Nasrabadi [28] stated that the three main parameters of imperialist competition algorithm (ICA) are specific to the test field. Siddiqui et al. [29] compared the performance of DE with PSO and CMA-ES. However, they have found that the DE presented better performance than the PSO and CMA-ES, but greater variance is observed. Algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), differential evolution (DE), and covariance matrix adaptation evolution strategy (CMA-ES) are becoming more and more popular day by day. Yet their efficiency and effectiveness are still not promising since the methods have many limitations. The main challenge faced by many researchers is to tackle highly multimodal optimization problem. For multimodal optimization applications, the study of Yang indicated that firefly algorithm is superior to existing metaheuristic algorithm [30]. Another study found that FA can manage highly non-linear multimodal optimization problems in a natural and efficient way since local attraction are more prominent than long-distance attraction [31]. From [32], it is clear that the Fire-

fly algorithm offers better performance than the optimization of particle swarms in solving noisy nonlinear problems. Hence, it is expected that well placement optimization can be tackled more efficiently by FA. Another challenge in this field is an expensive objective function which creates a major problem for metaheuristic algorithms as metaheuristic algorithms require many parameters to be tuned by running the algorithm many times. To alleviate the problem, crow search algorithm can be considered as it requires fewer parameters to adjust and is easier to implement (2 parameters). For the above reasons, the authors are motivated to apply FA and CSA to solve these problems. To the best of our knowledge, there have been no researches on the application of CSO and FA to deal with well placement optimization problem. Hence the novelty of this study includes the implementation of FA and CSO on well placement optimization. To provide enhancement in the results and to extract maximum NPV from input data an advanced algorithm has been employed in this research. Furthermore, a comparative study with other methods from the literature review will also be provided to validate the result. In past, most research work has reported the convergence curve to show the performance of the algorithm. However, the end result of the algorithm does not show the efficiency and effectiveness of the algorithm. Hence, in this study, to evaluate the performance of the proposed algorithms several criteria are considered.

The overall paper presentation can be categorized in the following manner: The first sections represents an overview and recent works on well placement optimization. Section 2 depicts problem formulation. The methodology of this study is presented in section 3. Section 4 represents the result analysis. Sections 5 concludes this study.

2. Well placement optimization problem formulation

The well placement optimization, in general, can be formulated as:

$$Max\, R(u^n) \tag{1}$$

$$R(u^n) = NPV(u^n) \tag{2}$$

Subjected to:

$$LB \leq u^n \leq UB, \forall n \in (0, 1, 2, 3, ..., N-1), \tag{3}$$

here u^n represents well coordinates, NPV presents net profit value, LB and UB are lower bound and upper bound of the reservoir respectively.

The prime motivation behind well placement optimization is to make sure that the expenditure remains minimum while maximizing the net profit. NPV changes randomly with the change of co-ordinates value hence well placement. The variables used in (4) are shown in Tab. 1 depicted from [6]. Eclipse simulation was used to calculate cumulative oil production, cumulative water production's value.

$$NVP = \sum_{i=1}^{T} \frac{Q_0 P_0 + Q_g P_g - Q_w C_w - OPEX}{(1+D)^i} - CAPEX \tag{4}$$

3. Methodology

Metaheuristic algorithms are stochastic algorithms and non-deterministic in nature. It was first developed in 1995 by Kennedy and Eberhart [33]. There are various types of metaheuristic methods like local search, simulated annealing, Tabu search, variable neighborhood search, Population-based or trajectory-based search, etc. And among the population-based search process, some of the most popular algorithms are – Genetic algorithm, Particle swarm optimization, etc. Metaheuristic provides more efficiency than heuristic algorithms.

Tab. 1: Variable used for NPV formulation.

Q_0 is cumulative oil production	OPEX is the operational expenditure
Q_w is cumulative water production	OPEX is the operational expenditure
P_0 is oil price	D is the discount rate
C_w is cost per unit volume of produced water	T is the number of years passed since the production has started
P_g gas price	Q_g cumulative gas production

3.1. Firefly algorithm

Firefly algorithm (FA) is one of the most popular swarm intelligence-based algorithms. The algorithm was first developed by Yang in 2008 as a solution for optimization related problems. Firefly algorithm mainly inspired by the way firefly beetle attract their mate. According to the algorithm, brighter fireflies attract the less bright fireflies. Similarly, the current best solutions lead the previous best solution towards the optimum output. Figure 1 shows the flow diagram of firefly algorithm. The brightness, β, and step length of each random movement, α^{t+1}, can be found as

$$\beta = \beta_0 e^{-\gamma r^2} \tag{5}$$

$$\alpha^{t+1} = \alpha^t \alpha_0. \tag{6}$$

At the beginning of the algorithm a random feasible solution is generated and after each iteration, it compares the present calculated solution with the previous one. Finally, the brightest of the acquired solutions will take the lead. for example, firefly i with less brightness will be attracted to a brighter firefly j according to (7) given as below-

$$X_i^{t+1} = X_i^t + \beta \left(X_j^t - X_i^t \right) + \alpha \varepsilon_i^t, \tag{7}$$

where

β_0: brightness of X_i at $r = 0$,

γ: An algorithm parameter which indicates how much a distant firefly is related with its nearest firefly.

α: step length of each random movement.

ε: a random vector from uniform distribution between 0 and 1.

3.2. Crow search algorithm

Crow search algorithm (CSA) is a population-based metaheuristic algorithm for solving optimizing solution of a practical problem. This algorithm was first developed by Askarzadeh [34]. Crow is one of the most cunning birds and possesses remarkable intelligence. They can recall faces or, objects, can communicate with other group members via some complex skills and hide and retrieve hidden food. The classical crow search algorithm was built based on the concept of how a crow hides its food and retrieve it later. Figure 2 represents the flow diagram of the crow search algorithm.

At first, crow selects a random place to hide their food. Secondly, crow analyses the quality of the selected place. Thirdly, crow starts finding out the place of food hidden by another crow. Finally, they monitor their caches to prohibit from being sneaked. In this way, they can remember their hidden food place for several weeks and find that food when necessary. Using their sharp memory crow also finds out the hidden food of another crow as well. If in an environment with d dimension and N number crows are present, then the position of crows i at iteration $iter$ is given by:

$$X^{i,itr} = \left[X_1^{i,itr}, X_2^{i,itr}, ..., X_d^{i,itr} \right],$$

where $i = 1, 2, ..., \& \, itr = 1, 2, ...$

Every crow flies around and searches for a better hiding place. Such individual searches can be termed as local search. And among the searches by a certain crow, the best possible place is selected. The same thing is applicable when a crow tries to find the hidden food of another crow. It starts following the target crow and monitors every position where that target crow flies to. And
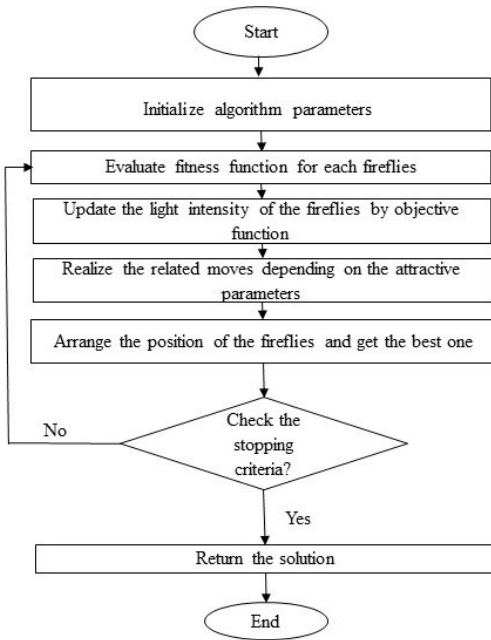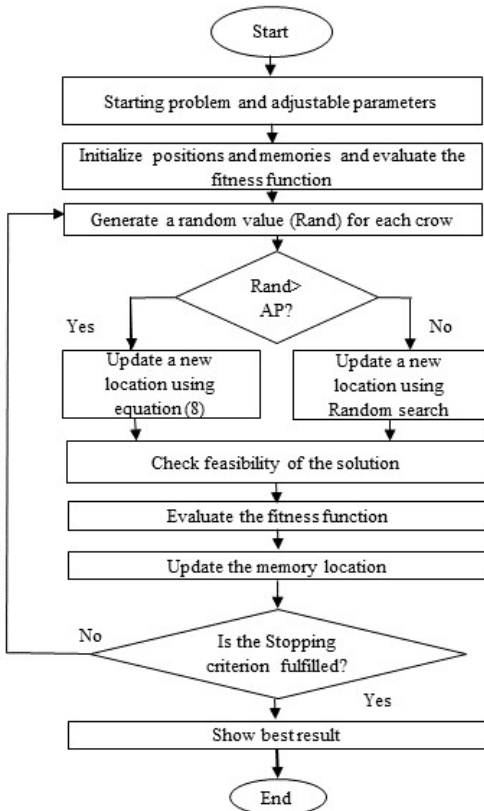
Fig. 1: Flow chart of Firefly algorithm.

Fig. 2: Flow chart of CSA.

out of those places, the crow finds out the hidden food and steal it.

In [18] Askarzadeh explained such a scenario with a beautiful example. Suppose crow j wishes to visit its cache $M^{j,itr}$ at $iter$ iteration. At the same time crow i starts following that crow to steal j's food. At this point, there may appear two possible solutions:

Case 1: When crow does not notice that it is being followed by crow i, crow j will lead crow i towards his hiding place. Position of crow i will be changed as follows :

$$X^{i,itr+1} = X^{i,itr}$$
$$+ r_i * f_l^{i,itr} * \left(M^{j,itr} - X^{i,itr} \right), r_i \geq AP_i^{itr}, \tag{8}$$

where r is a random number between 0 and 1 and $f_l^{i,itr}$ denotes the flight length of crow i at $iter$ iteration.

Case 2: Where memory $M^{i,itr+1}$ in (9) denotes the memory location of ith crow for $itr+1$ iteration. $M^{i,itr+1}$ is updated based on the following equation:

$$M^{i,itr+1} =$$
$$\begin{cases} X^{i,itr}; f(X^{i,itr+1}) \text{ is better than from } f(M^{i,itr}) \\ M^{i,itr}; \quad \text{othewise} \end{cases}$$
$$\tag{9}$$

Crow j knows another crow i is following it. Hence, to restrain its cache from being pilfered, crow j will fly to another position to confuse crow i using the following equation:

$$X^{i,itr+1} =$$
$$\begin{cases} X^{i,itr} + r_i * f_l^{i,itr} * \left(M^{j,itr} - X^{i,itr}; r_i \geq AP_i^{itr} \right) \\ \text{a random position in search space; otherwise} \end{cases}$$
$$\tag{10}$$

where r_i is a random number between 0 and 1 and AP_i^{itr} denotes the awareness probability of crow j at iteration $iter$.

4. Result analysis

4.1. Experimental setting

The simulator will provide production data for specific well placement. Matlab's optimization

Tab. 2: Economic Parameters used by authors in well placement optimization.

Economic parameter	Value	Unit
CAPEX	6.4E7	$
Oil price	290.572	$/STB
Gas price	0.126	$/MScf
Oil production cost	72.327	$/STB
Water production cost	31.447	$/STB
Discount rate	10%	-

algorithms will provide the specific location of the well. Figure 3 represents the overall flow diagram for searching the maximum net present value. In each trial, the number of iteration and the number of particles were 100 and 20 respectively for all algorithms. The economic parameters that were used in the (4) to conduct the experiment are listed in Tab. 2 and Tab. 3.
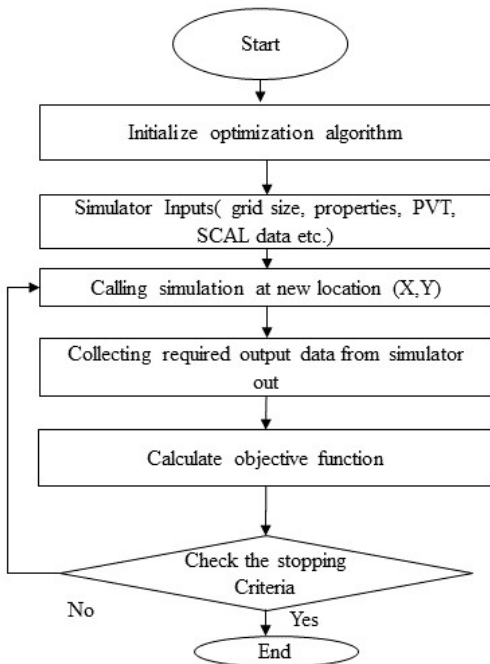

Fig. 3: A general flow chart for searching the maximum net present value.

4.2. Performance comparison criteria

To evaluate the performance of the algorithms several criteria was considered for this problem [36, 37]. So, authors have considered several criteria mentioned below:

Effectiveness is a simple measure of performance and is the average value between tests of the best solution found as a percentage of the global optimum or,

$$\overline{f} = \frac{1}{N} \sum_{i=1}^{n} N \frac{f(\hat{p}_i)}{f(p*)}, \quad (11)$$

where $f(p)$ is the value of solution p; $p*$ is the globally optimum solution; $\hat{p}_i$ is the best solution found in trial i and N is the number of trials for each algorithm.

Efficiency indicates the speed at which the algorithm reaches a performance level using the number of unique evaluations required to find a solution of at least 98% the best value of solution found, on average between tests or,

$$\overline{L} = \frac{1}{N} \sum_{i=1}^{n} N \frac{L_i^{98}}{M}, \quad (12)$$

where additionally, L_i^{98} is the number of unique function evaluations required to find solution q such that $f(q) \geq 0.98 f(\hat{p}_i)$ for trial i (for minimization) and M is the total number of function evaluations per trial.

Apart from these two criteria, statistical data like **standard deviation**, average and **min-max** are data are collected in experimental trials and the results are shown in Tabs. 4 and 6. 5 trials are considered for each algorithm to calculate the mentioned criteria.

Quality of the solution can be obtained from standard deviation. Lower standard deviation means the results of the algorithms are reliable.

Again, **Convergence curve** is one of the most important factors for evaluating the performance of an algorithm. Convergence curve reveals the convergence speed.

Tab. 3: Recently applied Metaheuristic algorithms on well placement optimization.

Ref.	Years	Technique	Parameter Configuration
1. [13]	2018	GA	Iteration=100 Swarm size=20 Crossover = 60% Mutation = 5%
2. [35]	2018	PSO	Iteration=100 Swarm size=20 Inertial factor = 0.729 c_1 & c_2=1.494 (Here c_1, c_2 represents acceleration)
3. Proposed	2012	FA	Iteration=100 Swarm size=20 The light absorption coefficient $\gamma = 1$ brightness of X_i at $r = 0$, $\beta_0 = 2$ Mutation Coefficient, alpha, $\alpha = 0.2$ Mutation Coefficient Damping Ratio, $\alpha_0 = 0.98$
4. Proposed	2016	CSA	Iteration=100 Swarm size=20 Flight length, $fl = 2$ Awareness Probability, Ap=0.3

4.3. Case study 1

To conduct the experimental test, the PUNQ-S3 reservoir model is considered. The PUNQ-S3 model is a synthetic reservoir model based on a real field used by Elf Exploration production. It was developed to test methods for quantifying uncertainty assessment. Details of the reservoir model can be found on [38]. The PUNQ-S3 has $19 \times 28 \times 5$ grid blocks. In this study, the authors considered 4 vertical wells to be optimized. Each well has coordinates (x, y). The total number of variables to be optimized in this experiment is therefore 2×4. The parameters that are used in this case study are listed in Tab. 3. The iteration number and population size for this case study is 100 and 20 repectively.

Statistical and convergence analysis
Convergence curve is an important tool to analyze the convergence speed of the algorithm and to compare its performance with other algorithms. So, plots of the average NPV of GA, PSO, CSA and FA algorithms versus the number of iterations are shown in Fig. 4. From Fig. 4 FA is superior to other algorithms for finding better NPV in the PUNQ-S3 reservoir. The second-best algorithm is GA. PSO achieved the third best NPV. GA and PSO both got stuck in local optima. Overall, in case study 1, FA has faster convergence and achieved the highest NPV. However, the CSA algorithm was not able to provide satisfactory NPV.

The results about the max, min, average, standard deviation, effectiveness, and efficiency of NPV for each algorithm are collected from trails and listed in Table . The results in case study 1 show that FF algorithm is best in 5 criteria. However, CSA had superior efficiency. The reason for this phenomenon is that efficiency is calculated with respect to its own best solution. So, despite having lower NPV than other algorithms CSA achieved higher efficiency. The box plot result shown in Fig. 5 depicts that FF has the lowest standard deviation with comparison to other algorithms.

Tab. 4: Statistical data of applied Metaheuristic algorithms on well placement optimization for PUNQ-S3 reservoir.

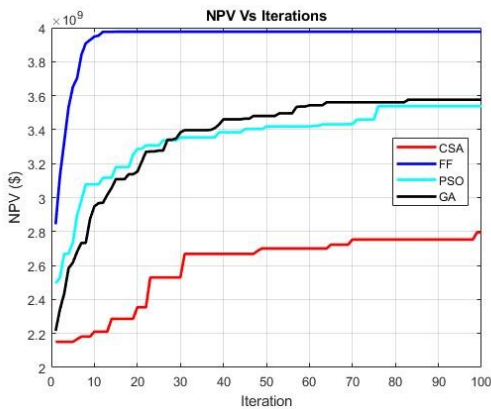|	GA	PSO	CSA	FF
Max	4.07E+09	3.93E+09	3.26E+09	4.00E+09
Min	3.24E+09	3.10E+09	2.43E+09	3.94E+09
Average	3.58E+09	3.54E+09	2.80E+09	3.98E+09
Standard deviation	3.48E+08	3.68E+08	3.92E+08	3.62E+07
Effectiveness	8.79E-01	8.69E-01	6.87E-01	9.77E-01
Efficiency	4.62E-01	5.00E-01	7.10E-01	5.58E-01

Fig. 4: Convergence curve for PSO, CSA, GA and FA.
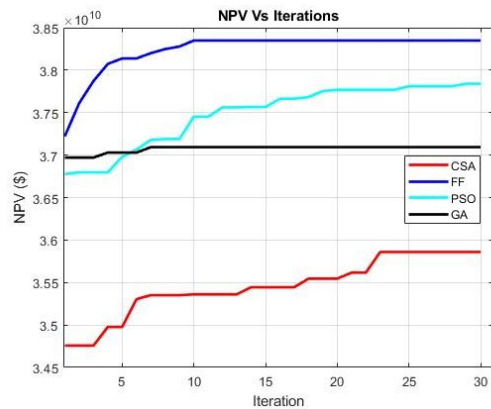

Fig. 6: Convergence curve for PSO, CSA, GA and FA.
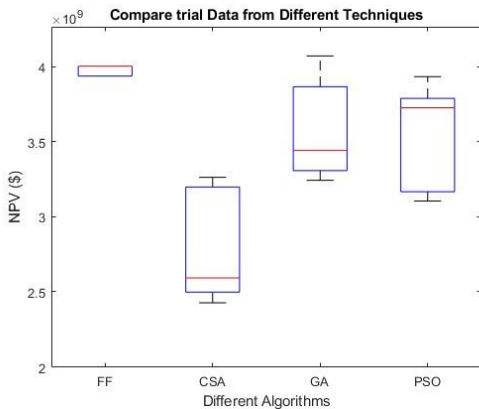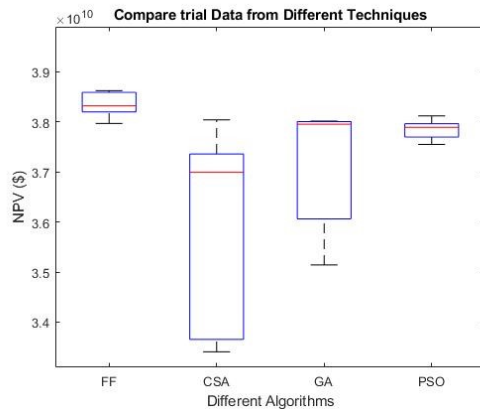

Fig. 5: Boxplot for PSO, CSA, GA and FA.

Fig. 7: Box plot for PSO, CSA, GA, and FA.

4.4. Case study 2

To carry out the second case study, the First SPE model is considered. The First SPE model is a synthetic reservoir model based on Three-Dimensional Black Oil Reservoir Simulation Problem. The First SPE model has $10\times10\times3$ grid blocks. In this study, the authors considered that 2 verticals well to be optimized. Each well has coordinates (x, y). The total number of variables to optimize in this experiment is therefore 2×2. Table 5 lists the parameter that are used in this experiment. In this case study the number of iteration is 30 and population size is 5 for each algorithm.

Statistical and Convergence Analysis
From Fig. 6, FA is superior to the other algorithms to find a better NPV in the SPE 1 reservoir model. The second-best algorithm is PSO. However , Crow search algorithm and GA got stuck in local optima. Overall, in case study 2, FA has faster convergence and has found the highest NPV. However, the CSA algorithm again has not been able to provide a satisfactory NPV in case study 2.

Again, the results concerning the max, min, average, standard deviation, effectiveness and efficiency of the NPV for each algorithm are collected from the trials and listed in Tab. 6. The results of the case study of 2 shows that the FF algorithm is better on 5 criteria. However, PSO had less standard deviation. The result of the box plot illustrated in Fig. 7 shows that PSO has the lowest standard deviation compared to other algorithms and FF has the second-lowest standard deviation.

4.5. Advantage and disadvantage of proposed techniques

By analyzing the main characteristics of the FA, the following three points for its success can be highlighted:

- FA can perform better than PSO, GA, and CSA to tackle highly nonlinear, multimodal optimization problem as FA can automatically subdivide its population into sub-

groups, since local attraction is stronger than long-distance attraction.

- To avoid premature convergence as those in PSO and GA, FA does not update its location based on the personal best information, and there is no explicit global best either.

- FA can work as a DE, SA, and PSO so it has full advantage of these three algorithms [31]. Also, by controlling the scaling parameter FA can adapt to the problem landscape.

No free lunch theorem (NFL) noted that no single algorithm can be best for all problems [39]. In this problem, PSO, GA, CSA, and FA have several benefits and drawbacks. In Tab. 7, the advantage and disadvantages of these algorithms are presented.

This study has limitations, as it is primarily focused on optimization methods. The optimization techniques can be compared with other metaheuristic algorithm in future. Also, History matching, and uncertainty are not considered in this study. Also, proper techniques can be applied

5. Conclusions

In this study, the firefly algorithm and crow search algorithm are implemented for well placement optimization and their application with respect to well placement optimization problem is investigated. Experimental results suggested that the firefly algorithm can find a better solution than popular algorithms. However, the crow search algorithm was unable to acquire good results in this problem. Due to strong attraction to local attractor, firefly has a strong local search capacity which helped it to tackle this multimodal problem more efficiently. While a higher net profit value is the focus of this study, several statistical criteria is also considered to evaluate the performance of the algorithms. Firefly algorithm has shown superior performance than PSO, GA, and CSA in those criteria. However, due to its extensive local search it will require more computational time [40]. But, in this problem, as the

Tab. 5: Recently applied Metaheuristic algorithms on well placement optimization.

Ref.	Years	Technique	Parameter Configuration
1. [13]	2018	GA	Iteration=30 Swarm size=5 Crossover = 60% Mutation = 5%
2. [35]	2018	PSO	Iteration=30 Swarm size=5 Inertial factor = 0.729 c_1 & c_2=1.494 (Here c_1, c_2 represents acceleration)
3. Proposed	2012	FA	Iteration=30 Swarm size=5 The light absorption coefficient $\gamma = 1$ brightness of X_i at $r = 0$, $\beta_0 = 2$ Mutation Coefficient, alpha, $\alpha = 0.2$ Mutation Coefficient Damping Ratio, $\alpha_0 = 0.98$
4. Proposed	2016	CSA	Iteration=30 Swarm size=5 Flight length, $fl = 2$ Awareness Probability, Ap=0.3

Tab. 6: Statistical data of applied Metaheuristic algorithms on well placement optimization for case study 2.

	CSA	PSO	FF	GA
Max	3.80E+10	3.81E+10	3.86E+10	3.80E+10
Min	3.34E+10	3.75E+10	3.80E+10	3.51E+10
Average	3.59E+10	3.78E+10	3.83E+10	3.71E+10
Standard deviation	2.13E+09	2.11E+08	2.64E+08	1.30E+09
Effectiveness	9.31E-01	9.80E-01	9.93E-01	9.61E-01
Efficiency	1.73E-01	1.30E-01	2.46E-01	1.00E-01

Tab. 7: Advantages and disadvantages of discussed techniques.

Techniques	Advantages	Disadvantages
GA	+ Easy to incorporate discrete decision variables. + Initializing itself from possible solutions. + Higher NPV is achieved than GA	+ Tuning the algorithm is hard. + The convergence and stability linked with the crossover and mutation rates. + Less efficient than PSO.
PSO	+ Less parameter to tune. + Simple structure and less dependent on initial points. + Incorporating discrete variable is easy.	+ Trapped in local optima due to weak local search. + A high standard deviation and low efficiency are observed.
FA	+ Low Standard deviation is observed + Better local search + With respect to standard deviation, efficiency and effectiveness Firefly algorithm is better than other three algorithms.	+ Computationally expensive + Extensive local search causes higher number of function evaluation
CSA	+ Less parameter to tune. + Faster convergence. + Easy Implementation.	+ Less effective in nonlinear Optimization. + Trapped in local Optima.

net profit value is counted in billions, higher net profit value is much more important than computational time. Future optimization studies should focus on combining the location of the well, well control parameters, and matching history. By harnessing equation less Convolutional Neural Network (CNN), we can retain the flexibility to quantify the uncertainty of different well-controls. For better approaches, researchers have recently merged quantum computing with current metaheuristic optimization algorithms. Quantum-based optimization techniques were applied in several complex engineering applications using quantum parallelism mechanism. Additionally, we suggest using the global search algorithm with a local search approach, because it may have the advantage of solving well placement optimization problem successfully. Lots of research papers have used proxy models in recent years to replace actual reservoir simulators, and these models have been found to minimize runtime. The accuracy of this alternative model therefore depends on its range of sampling. Future research in this area may focus on improving the reliability of this technique.

Acknowledgments

Nomenclature

ABC	Artificial Bee colony
C_w	Cost per unit volume of produced water ($/STB)
CSA	Crow Search Algorithm
CAPEX	Capital expenditure ($)
D	Discount rate (fraction)
GA	Genetic Algorithm
ICA	Imperialist Competitive Algorithm
MA	Metaheuristic algorithms
NPV	Net present value ($)
NFL	No Free Lunch theorem
O-CSMADS	Meta-optimized hybrid cat swarm MADS
OPEX	Operational expenditure ($)
PUNQ-S3	A synthetic Reservoir
PSO	Particle Swarm Optimization
P_o	Oil price ($/STB)
QPSO	Quantum Particle Swarm optimization
Q_w	Cumulative water production (STB)
Q_o	Cumulative oil production (STB)
PSO	Particle Swarm Optimization
SPE-1	A Synthetic Reservoir
T	Number of years
WPO	Well placement optimization

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