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Optimization of Lift Gas Allocation using Evolutionary Algorithms

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Abstract: In this paper, the particle swarm optimization (PSO) algorithm is proposed to solve the lift gas optimization problem in the crude oil production industry. Two evolutionary algorithms, genetic algorithm (GA) and PSO, are applied to optimize the gas distribution for oil lifting problem for a 6-well and a 56-well site. The performance plots of the gas intakes are estimated through the artificial neural network (ANN) method in MATLAB. Comparing the simulation results using the evolutionary optimization algorithms and the classical methods, proved the better performance and faster convergence of the evolutionary methods over the classical approaches. Moreover, the convergence rate of PSO is 13 times faster than GA's for this problem.

Keywords: particle swarm optimization; crude oil lifting; lift gas allocation; optimization; artificial neural network; genetic algorithm.

1. INTRODUCTION

There exist a wide variety of natural mechanisms to drive crude oil from the underground reservoirs to the surface, including the gas expansion and water pressure mechanisms. When the natural energies to produce crude oil from a well is not sufficient, the artificial lift procedures are used to accomplish the oil production process. In general, the artificial lift processes are divided into two main categories; gas-based lift process and pump-based lift process [1-8]. Gas-based lift technology is known as an efficient and economical procedure in the oil production industry. In a gas-based lift process, the optimal rate for the gas injection is determined such that it can compensate for the hydro-static pressure drop and frictional pressure drop in the well [9]. The optimum injection rate is important, mainly because of the operating constraints related to the available gas intake.

One of the very first studies on gas allocation optimization was conducted by Redden et al. in 1974 [10]. Authors in [10] have optimized the gas distribution among 30 wells in Venezuela. Their approach was based on the good laboratory practices (GLP) diagrams, and the optimization criterion was the higher profit rate. Their proposed strategy did not consider any optimization constraints; i.e., they assumed the unlimited amount of gas is available. A similar study is conducted by Mayhill in 1974 [11]. In 1981, Kanu and his colleagues introduced a parameter called the economic slope, which was a measure of the economic efficiency in a gas-based lift process. In their proposed approach, the optimal gas allocation was analyzed with and without constraints; e.g., with limited and unlimited gas intake [12]. In a further study, Nishikiori et al. developed a strategy based on the economic slope parameters, in which the optimum amount of gas injection was determined through a pseudo-Newtonian method [13]. In [14], authors optimized the controller tuning process using the particle swarm optimization. The objective of the optimization problem in their approach was to maximize the production rate. They also utilized GLP diagrams in their method. In another study, [15] developed a distributed algorithm to optimize the energy allocation in a building environment [15]. In [16], the rate of lift gas injection is determined based on the net present value (NPV). From their study, it is realized that the maximum profit from the production does not necessarily occur at maximum production. Authors also proved that the oil price is an important parameter in the optimization process, and an appropriate optimization scenario should be picked considering the oil price rate. However, the authors did not provide a well-designed model for their strategy. [17] applied the control theory principles to optimize the lift gas distribution; their approach was a cascaded control strategy. [18] developed an algorithm based on ant colony algorithm (known as continuous ant colony optimization, or CACO) to solve the gas allocation problem.

In this paper, the optimum amount of lift gas is distributed over a set of wells based on an evolutionary optimization algorithm. It is the first time that the particle swarm optimization (PSO) algorithm is used for finding the optimal gas injection rate for oil lift process. Worth mentioning that PSO algorithm is known to be more efficient and faster in solving such optimization problems, compared to the similar evolutionary algorithms such as genetic algorithm (GA). Moreover, in this study, the artificial neural network (ANN) method is utilized to estimate the performance plots of the gas-based lift process.

The rest of the paper is organized as follows. The next section explains the two evolutionary algorithms; genetic algorithm (GA) and particle swarm optimization (PSO). Section 3 describes the PSO algorithm challenges. The proposed strategy is shown in section 4. Section 5 includes the simulation results. The work finishes with the conclusions in section 6.

2. EVOLUTIONARY ALGORITHMS

In this section, the genetic optimization algorithm (GA) and the particle swarm optimization (PSO) algorithm are explained in detail.

2.1 Genetic algorithm

Genetic algorithm is one of the most important meta-heuristic algorithms, first introduced by Holland in 1975 [19]. Genetic algorithm is a type of evolutionary algorithm, which is commonly used in artificial intelligence (AI) and computing. The genetic algorithm applies a set of solutions to the optimization problem in each generation. The selection process chooses the individuals with the best fitness; these individuals mutate and reproduce new genes [20-26]. Therefore, the best optimum solutions are attained through mimicking the natural process genes mutation, selection, and reproduction. In the genetic algorithm, the final goal of selections and mutations is to maximize the fitness or minimize the costs of each individual. The genes adapt themselves to the environmental conditions such that they survive or mutate with genes with higher fitness. The crossover operator is used to produce new offsprings from every two parents.

2.2 Particle swarm optimization algorithm

Extensive studies have investigated the social behavior of various types of creatures; such as birds flock, school of whales, fish, sharks, etc. The particle swarm optimization (PSO) algorithm is a meta-heuristic computational method that mimics the social behavior of animal swarms. PSO optimizes problem by improving the candidate solution iteratively. The algorithm was first introduced by Kennedy and Eberhart in 1995 [27]. Swarm intelligence is the collective behavior of self-organized systems. The algorithms in artificial intelligence (AI) follow a hierarchy directly or indirectly. In PSO algorithm, two main parameters are being updated in each iteration; velocity term and position term. The particle's velocity and position are updated through the following equations, respectively.

$$v_i(t+1) = wv_i(t) + c_1r_1(y_i(t) - x_i(t)) + c_2r_2(\hat{y}(t) - x_i(t)) \tag{1}$$

$$\begin{aligned} x_i(t+1) &= x_i(t) + v_i(t+1) \\ x_i(t) &\in U[x_{min},\ x_{max}] \end{aligned} \tag{2}$$

where vi(t) and xi(t) denote the velocity and position of particles at time t. y and parameters represent the personal best solution of the particle and the global best solution, respectively. r1 and r2 are the random vectors with uniform distribution in the [0,1] interval. w, c1, and c2 are the inertia coefficient, personal learning coefficient, and collective learning coefficient, respectively.

Beside the velocity and position updates, the personal best and global best parameters should also be updated in a standard PSO algorithm.

$$\begin{aligned} &y_i(t+1) = y_i(t) \quad for f(x_i(t+1)) \geq f(y_i(t)) \\ &y_i(t+1) = x_i(t+1) \quad for f(x_i(t+1)) \leq f(y_i(t)) \\ &\hat{y}(t) = y_0, y_1, ..., y_z = min f(y_0(t)), f(y_1(t)), ..., f(y_z(t)) \end{aligned} \tag{3}$$

The PSO algorithm is as follows.

- For each particle $i \in 1, .., s$, initialize th position x_i and velocity v_i randomly.
- Set $y_i = x_i$.
- For each particle i, evaluate the fitness function $f(x_i)$.
- For each particle i, update y_i and $\hat{y}_i$ from (3).
- For each dimension $j \in 1, ..., N_d$, update the velocity from:

$$\begin{aligned} v_{i,j}(t+1) = &\, wv_{i,j}(t) + c_1r_{1,j}(y_{i,j}(t) - x_{i,j}(t)) \\ &+ c_2r_{2,j}(\hat{y}_j(t) - x_{i,j}(t)) \end{aligned} \tag{4}$$

- Apply the position update to each particle.
- Stop the algorithm when the convergence criteria is met, otherwise, go to step 3.

3. PARTICLE SWARM OPTIMIZATION ALGORITHM CHALLENGES

The particle swarm optimization algorithm has several drawbacks and disadvantages. PSO can easily fall into the local optimum points in high-dimensional optimization problems. Although PSO is faster compared to similar evolutionary algorithms, its convergence rate does not enhance with a higher number of iterations. The prominent reason is that in this algorithm, particles converge to the point with the personal best and global best solution. To address this issue, the inertia weight w is used to modify the algorithm [28]. Another main drawback in this algorithm is that the quality of solutions is very much dependent to the weighting coefficients and algorithm parameters [29]. Therefore, we should try to tune the PSO parameters in the best way.

4. PROPOSED STRATEGY

In order to define the optimization problem, we first need to estimate the performance diagrams of the wells with different levels of gas injections. The artificial neural network (ANN) algorithm is utilized in this step to attain the (good laboratory practices) GLP-based performance diagrams. The training model is then used as the fitness function in the optimization process. Once the convergence criteria are met, the algorithm stops. The PSO algorithm is simulated in MATLAB environment. The advantages of coding in MATLAB include:

- The programmer can do the code testing, implementing, visualizing easily and fast without the need for sophisticated, time-consuming programming.
- MATLAB includes a large database of built-in algorithms and libraries. It also includes various embedded functions and tools; such as linear algebra function, neural network tools, probability functions, etc.
- The programmer can utilize the advanced programming techniques and object-oriented programming.
- The programmer can easily integrate MATLAB with other programming languages, or software. Also, the programmer is able to export to or import in any files between MATLAB and other software.

5. SIMULATION RESULTS

In this section, the results of gas allocation optimization using PSO algorithm are presented and discussed. Two different scenarios; a low-dimension problem with six wells, and a high-dimension problem with 56 wells are considered in our simulations. The constraints on the amount of available lift gas are considered (limited amount of lift gas is available). The optimization is implemented on the datasets from Buitrago et al. research. As mentioned, the ANN approach is employed to estimate the performance diagrams of the lift gas. The objective in the constrained optimization problem is to maximize oil production. The upper limit for the gas consumption is only considered as a constraint, and the gas consumption is not a term in the objective function. The objective function and the constraints equation is as (5).

$$maxZ = \sum_{i=1}^{\#ofwells} Q_{o_i}$$
$$\sum_{i=1}^{\#ofwells} Q_{g_i} \leq AG \tag{5}$$

The simulation results for the six-well problem and 56-well problem, using the proposed approach and GA, are shown in Tables 1 and 2, respectively.

Moreover, the estimation of performance plots using the neural network approach are illustrated in Figure 1.

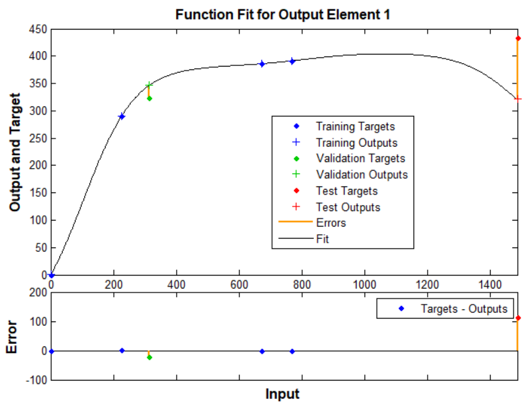

Figure 1: The performance plot estimates through the ANN algorithm.

Table 1: Simulation results on a 6-well problem using the propose method and GA

Well 1	$q_g(MSCF/D)$	$q_0(B/D)$
PSO	296.6	335
GA	296.6	335
Well 2	$q_g(MSCF/D)$	$q_0(B/D)$
PSO	507.7	720
GA	507.7	720
Well 3	$q_g(MSCF/D)$	$q_0(B/D)$
PSO	931.7	1079
GA	934.8	1079
Well 4	$q_g(MSCF/D)$	$q_0(B/D)$
PSO	353.9	534
GA	353.9	534
Well 5	$q_g(MSCF/D)$	$q_0(B/D)$
PSO	910.0	757
GA	910.0	757
Well 6	$q_g(MSCF/D)$	$q_0(B/D)$
PSO	3000.0	3425
GA	3000.0	3425

Table 2: Simulation results on a 56-well problem using the propose method and GA

	$q_g(MSCF/D)$	$q_0(B/D)$
PSO	22500	22541
GA	22500	22541

From Table 1, the optimum oil production is 3425 barrels in the constrained optimization problem, in both PSO and GA approaches. In a 6-well optimization problem, the results from the two evolutionary algorithms GA and PSO is almost the same, since it is a low-dimension problem. Obviously, in a higher dimension optimization problem with more computational complications, the performance of the evolutionary optimization methods will be recognizably different. Comparing the results of simulations in a 56-well problem proved that the proposed evolutionary algorithms performed more than 3% (more than 700 barrels) better than the classic approaches. Therefore, if the higher the dimension of the problem, the significantly better performance will be attained using the evolutionary optimization algorithms compared to the classical methods.

Although the results from GA and PSO approaches are the same, we recommend PSO for the gas allocation optimization problem. To prove the superiority of PSO over GA, we have shown the number of iterations needed to solve the same problem using the two algorithms (Figure 2). Thus, from the iteration graph, PSO converges a lot faster (13 times faster) than GA and requires less number of iterations for solving the same optimization problem. So, the operational costs for solving the problem using GA is significantly more than the cost associated with PSO. The parameter update processes in

PSO enhances the convergence pace in the algorithm. The main drawback of GA in this regard is that it does not update its parameters, and it does not include any tunable parameter in its process.

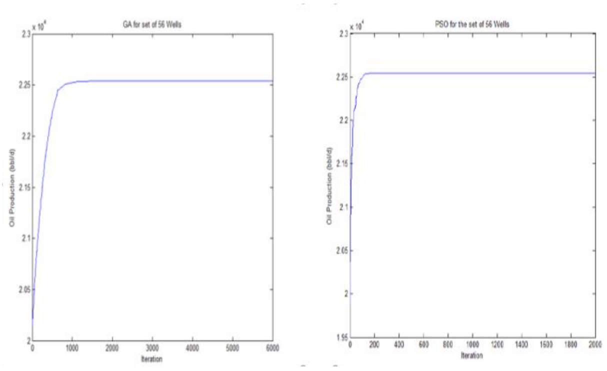

Figure 2: The number of iterations in PSO and GA for solving the 56-well problem

6. CONCLUSIONS

The gas distribution optimization problem is studied in this paper. The particle swarm optimization (PSO) approach is used for the first time for this problem. The performance plots are attained through an artificial neural network (ANN) learning. The proposed strategy is implemented on a high-dimensional (56-well) and a low-dimensional (6-well) problem. The better performance of the evolutionary optimization method (GA and PSO) over the classical approaches is more recognizable when the problem is of higher dimension (like the 56-well problem). PSO and GA showed similar performances; however, PSO performed much faster (13 times faster) and required less number of iterations than GA.

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