[Regular Paper]

Genetic Algorithms and Ant Colony Approach for Gas-lift Allocation Optimization

Mohammad M. ZERAFAT, Shahab AYATOLLAHI*, and Ali A. ROOSTA

EOR Research Center, School of Chemical and Petroleum Engineering, Shiraz University, Shiraz, IRAN

(Received July 8, 2008)

Continuous gas-lift is one of the most commonly practiced artificial lift techniques. It assists production enhancement by continuous injection of high-pressure gas into the well tubing, which lightens the oil column. Either gas limitation or compressor capacity makes it impossible to make all the network wells produce at the optimum rate; hence the need to determine the optimal gas distribution. Gas allocation optimization is a type of nonlinear function maximization with gas injection rates as decision variables subject to physical restrictions. Various optimization methods are applied in previous works among which genetic algorithm (GA) has proposed the best efficiency for large networks. In this work, various methods are performed as a comparison to GA. Besides, ant colony optimization (ACO) is applied to the network as a new optimization tool in oil industry, as a possible alternative for GA, already proved its capability in the optimization of water distribution networks. The literature demonstrated the application capability of GA and ACO for gas-lift allocation optimization in small networks. The results proved an availability of GA and ACO for this problem, and it showed the applicability to the optimization of large-scale networks. The results are compared to similar calculations in the literature by other optimization techniques, which show promising agreement.

Keywords
Oil production, Gas-lift, Genetic algorithm, Ant colony optimization

1. Introduction

Continuous gas-lift consists of high-pressure gas injection into the well tubing to lighten the oil column and hence enhance well production[2),3),17)]. Excess gas injection is uneconomical as a result of gas price, compression expenses and the possible production reduction due to induced pressure drop in the well tubing. Inappropriate gas distribution to the oil-well network with limited available gas also reduces production and profitability[19),21)]. The optimal allocation of a limited amount of gas to the well network, poses the gas-lift optimization problem. While for a single well or other small networks, simple nodal analysis can be adequate, large complex systems entail much more complex optimization approaches[1),6),24)]. Various optimization techniques are examined in the literature; both derivative-based such as sequential linear programming (SLP)[18)], sequential quadratic programming (SQP)[22)] and generalized reduced gradient (GRG)[25),26)] and stochastic methods such as genetic algorithm (GA)[16),20)].

Although classic derivative-based techniques prove to be capable of handling gas-lift optimization problem, in large networks they take much time and iteration procedure to determine the optimal allocation. As a result, stochastic techniques are advised to be applied to large networks. In this paper, stochastic optimization techniques such as GA and ACO are applied to gas-lift optimization problem and compared to classic derivative-based methods performed earlier in the literature.

2. Network Optimization

An oil production network consists of a number of wells interconnected through a combination of pipelines and compresors. The production of each individual well in the network is affected by the back pressure induced by other wells. It is common to neglect this effect if the network is small or the pipelines are not so long as to induce a considerable pressure drop to the network. In this case each well can be considered to be non-affected by other wells in a production network and the GLPCs can be plotted individually. A simplified well network under gas-lift facilities is presented in **Fig. 1**.

The individual GPLC curve can be obtained by simulation using field specifications, oil-well dimensions and fluid properties. These discontinuous points are fitted to be used as the feed to the optimization prob-

* To whom correspondence should be addressed.
* E-mail: shahab@shirazu.ac.ir

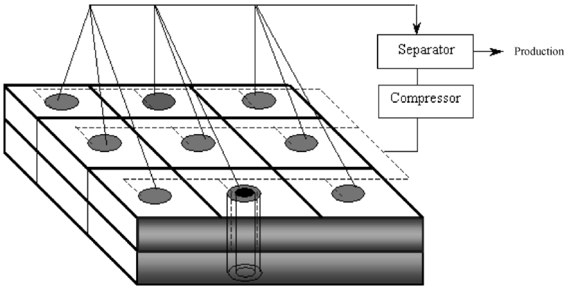

Fig. 1 Network under Gas-lift Facilities

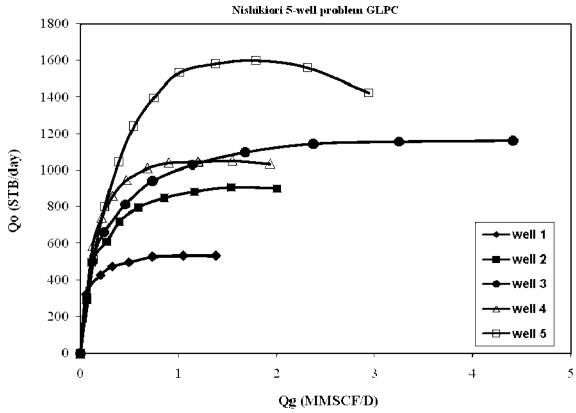

Fig. 2 The GLPCs for Nishikiori's 5-Well Problem

lem. Equation (1)[1] is suggested to be helping:

$$Q_o = c_1 + c_2 Q_g + c_3 Q_g^2 + c_4 \ln(Q_g + 1) \quad (1)$$

Q_o, is the oil production rate (STB/D) and Q_g the gas injection rate (MMSCF/D) and also c_1 to c_4 are dimensionless constants.

The total oil production from a network of n wells, which is the sum of individual well productions, is a function of gas injection rate to the wells and can be shown as follows:

$$Q_{oT} = \sum_{i=1}^{n} Q_{oi} = f(Q_g) = f(Q_{g1}, Q_{g2}, ..., Q_{gn}) \quad (2)$$

Gas injection rates can be shown by some n dimensional column vector:

$$Q_g = (Q_{g1}, Q_{g2}, ..., Q_{gn})^T \quad (3)$$

Hence, the gas allocation optimization problem to produce the maximum oil production can be written:

$$Max\, Q_{oT} = \underset{Q_g}{Max}\, f(Q_g) \quad (4)$$

By the following constraints:

$$\sum_{i=1}^{n} Q_{gi} \leq Q_{g\ \mathrm{Available}} \quad (5)$$

$$Q_{gi} \geq Q_{gi\ \min} \quad i = 1, 2, ..., n \quad (6)$$

$$Q_{gi} \leq Q_{gi\max} \quad i = 1, 2, ..., n \quad (7)$$

It is worth mentioning that the wells are naturally producing or almost dead at the time the gas-lift process is initiated. When the production is dead there is always a minimum amount of injection needed to restart the oil production shown by $Q_{g\ \min}$. There is also a maximum amount, a balance between gravitational and frictional forces, beyond which the gas injection causes the oil production to get reversed shown by $Q_{g\ \max}$. A sample problem found in the literature is the Nishikiori's 5-well problem. The problem consists of 5 wells interconnected with GLPCs presented in **Fig. 2**. The purpose is to find the minimum gas injection rate that maximizes the oil production rate. The parameters for this problem are also given in **Table 1**.

3. Genetic Algorithm

Genetic algorithm (GA) is a robust search technique, utilizing the analogies to biology and genetics. Survival of the fittest among a population of individuals, selection, and reproduction strategies are concepts borrowed from natural processes and utilized as operators in the GA[13),14)]. A defined fitness function determines the capability of the parents to produce the next generation or to be omitted. Possible reproductive strategies are a combination of reproduction, mating or crossover and mutation. One of the easiest ways to apply the reproduction operator is the roulette wheel selection. In this way an individual vector of parameters could be analogous to a chromosome[4),9)].

The n-point crossover determines random crossover sites on the entire chromosome, while the uniform crossover generates one bit at a time. Each bit is inherited from one of the parents according to the crossover probability. Mutation is designed to avoid the loss of valuable genetic material, which may result from reproduction and crossover[12),14)]. Mutation's unique role is to create a mechanism by which information or small segments of parameter strings can be reinserted into a population. Mutation is highly disruptive by nature and the assumption of very low values is recommended. Strategies with no crossover and high mutation rate may produce a fairly robust search[10),23)].

The data needed to produce the best results by applying GA to gas-lift allocation optimization problem is also given in **Table 2**.

4. Ant Colony Optimization

ACO is a subset of swarm intelligence, in which ants act as agents and analogies to social insects' behaviors are used to handle the optimization problems. Any individual ant chooses one path randomly among all possible routes from the nest to the food source. Each ant contributes its own experimental data to the colony,

Table 1 Well Data for Example 5-Well System[19)]

		Well 1	Well 2	Well 3	Well 4	Well 5
1. Well depth	[ft]	7000	6000	7000	7500	8000
2. Reservoir pressure	[psia]	2500	2100	2500	3000	3200
3. Bubble point pressure	[psia]	1400	1200	1500	1800	2000
4. Formation gas liquid ratio	[SCF/STB]	250	100	100	75	100
5. API oil gravity	[API]	30	32	35	25	30
6. Water cut	[%]	50	25	25	50	50
7. Bottom hole temperature	[°F]	150	160	170	180	200
8. Well head temperature	[°F]	110	100	100	100	120
9. Tubing I.D.	[inch]	1.995	1.995	2.441	2.441	2.992
10. Casing I.D.	[inch]	4.500	4.500	5.500	6.000	6.000
11. P.I.	[STB/D/psi]	1.00	2.00	2.00	1.50	1.00
12. Well head flowing pressure	[psia]	200	200	200	200	200
13. Specific gravity of produced water		1.07				
14. Specific gravity of injected gas		0.70 at 14.7 psia and 60°F				
15. Surface operating gas pressure		1200 psia				
16. Well deviation		Straight well				
17. No mandrel in-place, no safety valve, no flow-line						
18. Inflow performance below bubble point is given by Vogel's equation						

Table 2 The Optimal Parameters for GA

Primary population	Crossover	Mutation	Iteration
20	0.8, 2-points	0.2, Gaussian	51

through indirect communication by pheromones and foraging behavior, thus the colony determines the shortest path between the nest and the food source over time. Because more trips may be made along shorter paths the ever-inreasing pheromone density attracts other ants to these paths. Besides, shorter paths will retain higher pheromone densities as a result of pheromone density decrease over time due to evaporation. The shortest path represents the global optimum and all the possible paths represent the feasible region of the problem[5)].

The first ant colony simulation algorithm was developed by Dorigo[7)] to solve the classic traveling salesman problem (TSP) in 1992. In the TSP, the goal is to find a closed tour of minimal length passing through n given cities while each city must be visited once and only once. Dorigo compared the results of their ACO algorithm applied to the TSP problem with a genetic algorithm. Results from several types of TSP problems show that ACO can identify solutions better than the GA. Gutjahr proved that under certain conditions, solutions from ant-based optimization converge to the global optimum with a probability close to unity[11)].

In the TSP, Each ant in city i places pheromone on a visited path, and then chooses to visit the next town j with a probability that is a function of the town distance, d_{ij} and of the pheromone density. τ_{ij}, represents the pheromone on edge (i, j) at iteration, t, which is updated according to the equation:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} + e \bullet \Delta\tau_{ij}^{e} \tag{8}$$

$(1-\rho)$, represents the decay of pheromone between iterations t and $t+1$, and

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{9}$$

Where $\Delta\tau_{ij}^{k}$ is the change in pheromone due to ant k selecting city j; and m is the total number of ants in one colony. The quantity $\Delta\tau_{ij}^{k}$ is given by

$$\Delta\tau_{ij}^{k} = \begin{cases} Q / L_k & \text{if ant } k \text{ uses edge } (i, j) \text{ in the iteration } t \\ 0 & \text{else} \end{cases} \tag{10}$$

Where Q is a constant related to the quantity of trail laid by ants, L_k is the total tour length by ant k. The 3rd part is called elitist ant strategy, where, e is coefficient of elitist pheromone, it is a small integer; $\Delta\tau_{ij}^{e}$ is the pheromone of best ant at each iteration, $\Delta\tau_{ij}^{e} = Q/L_e$ where L_e is the total tour length by elitist ant. This will direct ants' colony toward the best solution with higher a possibility. Next, the ant can decide the next city j from i by transition rule by the following Eq. (11):

$$P_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha}(\eta_{ij})^{\beta}}{\sum_{k \in \text{allowed}} [\tau_{ij}(t)]^{\alpha}(\eta_{ij})^{\beta}} \tag{11}$$

Where, defines the "visibility" η_{ij} as $1/d_{ij}$, d_{ij} is the distance between two cities. α and β are parameters that control the relative important of pheromone and visibility. The translation probability is a trade off between the visibility, which is greedy heuristic strategy, and the pheromone[15)].

ACO with its simpler algorithm and high optimum searching capacity can be compared to genetic algorithm as a possible alternative in analogous problems. ACO is applied to the network as a new optimization tool in oil industry, which has already proved its capability in the optimization of water distribution networks.

5. Results and Discussion

In order to check the compatibility of GA to solve gas-lift optimization problem, Nishikiori's 5-well problem is solved and the results are compared to previous gradient optimization techniques. The objective function can be considered to be $1/Q_o$ that is to become minimal through a stochastic search procedure. The results obtained by GA optimization after 51 generations are given in **Table 4**. As it is obvious from **Table 4** the results produced by GA lie between GRG and SQP that is; GA gives a higher production rate than SQP but fewer than GRG. GA mainly shows its capability in large production networks where the gradient methods either fail or drown into rigorous manipulations. **Figure 3** represents the best component in each iteration and is also compared to the average value in the generation. The minimal value in successive generations decreases till finally stopping at a general value. **Figure 4** shows the number of children and it is obvious, as the children number reaches 1 or 2 the algorithm has achieved steadiness. The optimal parameters for GA are also given in **Table 2**.

Another stochastic search technique applied to gas-lift optimization problem is ACO. **Figure 5** shows a schematic view of the way ACO can be applied to a gas-lift optimization problem. Each ant selects a random path on the well network. Initially, a homogeneous amount of pheromone is poured on all paths hence the equal probability of all paths to be chosen. By pass of time the iterative procedure causes the most chosen paths to attain higher pheromone concentrations and as a result attracting more ants. Relative gas injection represents the available gas division among the individual wells and the sum of these relative amounts equals or is less than the available gas. In this way, the optimal path which is the minimum gas injection

Table 3 The Optimal Parameters for ACO

No. of ants	τ_0 (initial phermone)	ρ_0 (evaporation rate)	Iteration
30	0.4	0.2	100

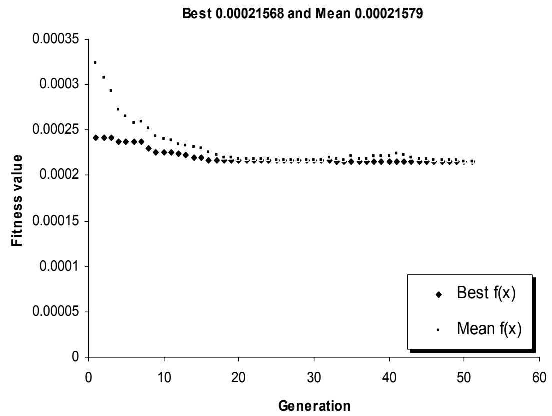

Fig. 3 The Best Offspring and the Average in Successive Generations

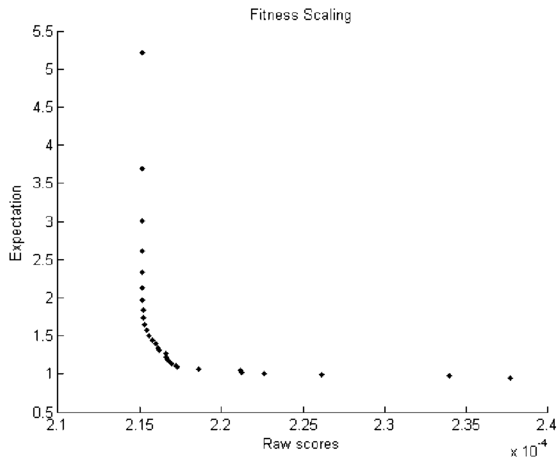

Fig. 4 The Number of Offspring *vs.* Objective Function Value

Table 4 The Comparison of Results with Nishikiori's[1)] 5-Well Problem

Gas availability = 3 MMSCF/D								
Well	SQP[1)]		GRG[25),26)]		GA		ACO	
	Q_g [MMSCF/D]	Q_o [STB/D]	Q_g [MMSCF/D]	Q_o [STB/D]	Q_g [MMSCF/D]	Q_o [STB/D]	Q_g [MMSCF/D]	Q_o [STB/D]
1	0.2630	440.560	0.2327	439.350	0.1952	425.22	0.1950	425.2
2	0.5574	977.418	0.5901	805.213	0.6140	813.41	0.6140	813.4
3	0.8840	1466.55	0.7288	925.676	0.6605	897.31	0.6600	897.3
4	0.5855	787.390	0.5452	977.986	0.6268	1007.29	0.6260	1007.2
5	0.7100	917.770	0.9032	1500.212	0.9034	1500.30	0.9030	1500.0
Total	3.0000	4589.688	3.0000	4648.400	3.0000	4643.60	3.0000	4643.0

MMSCF/D = 0.0283169×10^6 Sm^3/D.
STB/D = 0.158987 Sm^3/D.

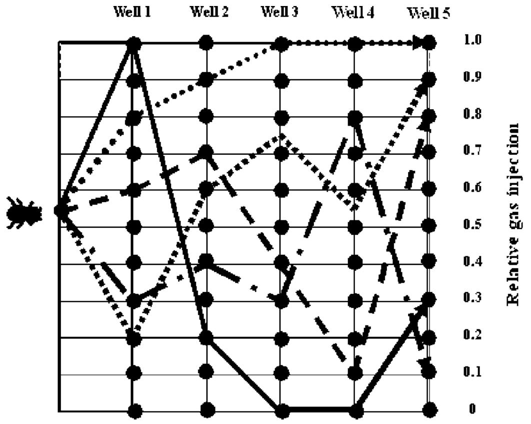

Fig. 5 Ant Colony Schematic of Gas-lift Problem

and highest oil production is determined. The optimal parameters used in ACO are given in **Table 3**.

A comparison between the number of iterations taken to produce the final results, says that GA has a better effcincy to solve the optimization problem. It is worth mentioning that the modified types of ACO may result in better calculations compared with GA.

6. Conclusions

(1) The small-scale network optimization problem was able to be solved by GA and ACO by shorter calculation time or less number of iterations than by SQP and GRG.
(2) Possibility of GA and ACO applications to a large-scale network optimization problem was revealed.
(3) It would be preferable for large networks to be optimized by stochastic methods rather than gradient techniques.

<SI unit conversion factor>
inch × 2.54 E-02 = m
ft × 3.048 E-01 = m
MMSCF × 1.0 E + 06 = ft^3
ft^3 × 2.831685 E-02 = m^3
Bbl × 1.589874 E-01 = m^3
psi × 6.894757 E + 03 = Pa
141.5/(131.5 + API) = g/cm^3
(°F − 32)/1.8 = ℃

References

1) Alarcon, G. A., Torres, C. F., Gomez, L. E., *J. Eng. Res. Tech.*, **124**, 262 (2002).
2) Ayatollahi Sh., Tauseef, S. M., Guzman, C., *Oil & Gas J.*, Jan. 10th, 37 (2005).
3) Bahadori, A., Ayatollahi, Sh., Moshfeghian, M., Asia Pacific Improved Oil Recovery Conference, Malaysia, 8-9 Oct., SPE 72169, (2001).
4) Bittencourt, A. C., PhD thesis, Stanford Univ., 1997.
5) Bonabeau, E., Dorigo, M., Theraulaz, G., *Nature*, **406**, (6), 39 (2000).
6) Buitrago, S., Rodriguez, E., Espin, D., Gas Technology Conference, Canada, SPE 35616, (1996).
7) Dorigo, M., PhD thesis (in Italian), Italy, 1992.
8) Dorigo, M., Gambardella, L. M., *Bio-Sys.*, **43**, 73 (1997).
9) Eshelman, L., Schaffer, J., Caruana, R., 3rd International Conference on Genetic Algorithms, Morgan Kaufmann Publishers, Inc., San Mateo, USA, 10 (1989).
10) Fogel, D., Atmar, J., *Bio. Cybernetics*, **63**, 111 (1990).
11) Gutjahr, W. J., *Future Gen. Com. Sys.*, **19**, 873 (2000).
12) Goldberg, D. E., Deb, K., "Foundations of Genetic Algorithms," Morgan Kaufmann Publishers, Inc., San Mateo, USA, (1994), p. 69.
13) Goldberg, D., "Genetic algorithms in search, optimization, and machine learning," Addison-Wesley, Reading, USA (1989).
14) Holland, J., "Adaption in Natural and Artificial Systems," MIT Press, Cambridge, USA (1975).
15) Li, Y., PhD thesis, Florida State Univ., (2006).
16) Martinez, E. R., Moreno, W. J., Moreno, J. A., Maggiolo, R., SPE Latin America/Caribbean Pet. Eng. Conf., Argentina, SPE 26993, (1994).
17) Mayhill, T. D., SPE 49th Annual Fall Meeting, Houston, SPE 5151, (1974).
18) McKie, C. J. N., Rojas, E. A., Quintero, N. M., Fonseca, J. R. C., Perozo, N. J., SPE Production and Operations Symposium, Oklahoma, SPE 67187, (2001).
19) Nishikiori, N., M. Sc. thesis, Univ. of Tulsa, 1989.
20) Ray, T., Sarker, R., *J. Petrol. Sci. Eng.*, **59**, 84 (2007).
21) Redden, J. D., Glen, T. A. S., Blann, J. R., Fall Meeting of the SPE (AIME), Texas, SPE 5150, (1974).
22) Roy, K. D., Kattapuram, J., SPE Western Regional Meeting, California, SPE 38333, (1997).
23) Schaffer, J., Caruana, R., Eshelman, L., Das, R., Proc. of the 3rd International Conference on Genetic Algorithms, Morgan Kaufmann Publishers, Inc., San Mateo, USA, 51 (1989).
24) Wang, P., Litvak, M., Aziz, K., Annual Tech. Conf. & Exhib., Texas, SPE 77658, (2002).
25) Zerafat, M. M., M. Sc. thesis (in Persian), Shiraz Univ., Iran, 2008.
26) Zerafat, M. M., Jeirani, Z., Ayatollahi Sh., Jahanmiri A., 5th Int. Chem. Eng. Cong. & Exhib., Iran, Kish Island (2008).

要　　旨

ガスリフト配置の最適化に用いる遺伝子アルゴリズムとアントコロニー手法

Mohammad M. ZERAFAT, Shahab AYATOLLAHI, Ali A. ROOSTA

EOR Research Center, School of Chemical and Petroleum Engineering, Shiraz University, Shiraz, IRAN

連続ガスリフトは最も普通に使われている人工採油法の一つである。高圧ガスを連続注入することによって，チュービング内の油カラムを軽くし，油増産に寄与する。ガス量の制限あるいはコンプレッサー能力の制限によって，ネットワーク内にある全坑井からすべて最適レートで油を生産することはできない。そこで，最適なガス量配分が必要になる。ガス量配分最適化は，機械的な制限を受ける変数であるガス注入レートを調整することによって，最大化を図る非線形問題である。さまざまな最適化手法が今まで適用されてきた。そのうち，大きなネットワークに対しては，遺伝子アルゴリズムが最も効率がよいとされている。本論文では，遺伝子アルゴリズムと比較するために，いろいろな手法を試した。その中でも，石油開発業界では新しい手法であるACO（Ant Colony Optimization）手法を，水攻水・産出水配分ネットワークの最適化手法として既に能力が認められている遺伝子アルゴリズムに替わるものとして，適用してみた。文献によると，遺伝子アルゴリズムもACO手法もガスリフトの配分最適化問題では，小さなネットワークで有効とされている。本論文では，ガスリフトへの遺伝子アルゴリズムとACO手法による最適化は，大規模ネットワークでも適用性があることが示された。結果は，文献にある類似の最適化計算結果と比較して，よい一致をみた。

……………………………………………………………