International Journal of Applied Science and Mathematics
Volume 3, Issue 1, ISSN (Online): 2394-2894

Application of Hybrid Genetic Algorithm in the Optimal Petroleum Production

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***Abstract* – Models of petroleum production system are very complex and iterative in nature with very rough surface involving several minimal and maximal points. Numerical optimization using gradient-based methods has high tendency of entrapping in a local optimum. Gradient-free optimization methods such as genetic algorithm (GA) are capable of locating the region of a global optimum but are very slow. So, integrating GA with a local optimizer can enhance its efficiency. In this work, optimization of petroleum production system was carried out using hybrid genetic algorithms (HGA). Sequential quadratic programming (SQP) was used as the local method for optimizing four components of the system which include the well tubing diameter, choke size, flowline size and separator pressure. The methodology has proven to be efficient for all considered cases.**

***Keywords* – Choke, Genetic Algorithms, Optimization, Petroleum Production, Separator, Sequential Quadratic Programming.**

I. Introduction

Petroleum production involves two distinct but intimately connected general systems: the reservoir, which is a porous and permeable underground formation containing hydrocarbon trapped by impermeable rock or water formation; and the artificial structures, which include the well, bottomhole and well head assemblies [1]. The surface gathering includes separation and storage facilities. Oil or gas production system consists of the reservoir, well, flowlines, separator, pumps and transportation lines. The reservoir stores the hydrocarbon fluids and supplies it to the well. The well provides the path and means of control of the flowing fluid from bottomhole to the surface. The flowlines transfer the fluid from well to separator. In the separator, gas and/or water is removed from the oil. The oil and gas are moved by pumps and compressors to store tanks or sales points via pipelines [2].

The optimization of this production system is very important. Optimization is the process of adjusting the inputs to or characteristics of a device, mathematical process, or experiment to find the minimum or maximum output or result [3]. The use of optimization strategy in upstream sector of petroleum industry can be traced as far back as 1950's with new algorithms being explored [4]. The fields of interest that are optimized include planning, drilling, history matching, well placement, recovery processes, facility design and operation and many other aspects. Several optimization techniques are employed for this purpose such as linear programming, integer programming, and nonlinear programming [5]. Genetic algorithm (GA) is one of the direct search optimization techniques which do not require gradient information of the objective function in their applications.

Genetic algorithm was first developed by [6] and popularized by [7]. It is an evolutionary algorithm that uses the idea of natural selection and genetics for optimal point selection [8]. GA begins with an initial set of random solution called population. The population is made up of individuals called chromosomes. For a binary GA, each chromosome is a string of binary bits. The chromosomes are formed via iterations in sequence. Each iteration is regarded as a generation where the chromosomes are evaluated and ranked according to their fitness value. The algorithm moves to the next generation to create new set of chromosomes called offspring. Offsprings are created by either merging two chromosomes together from current generation using a crossover operator or modifying a chromosome using a mutation operator. A new generation is usually formed from a mixture of parent and offspring chromosomes. Parent or offsprings are selected based on their fitness values. It is actually a survival of the fittest. Lesser fit chromosomes are rejected to keep the population size constant. The algorithm runs for a number of times and eventually converges to a possible optimal point [9]. GA has found wide range of applications in the optimization of petroleum production system.

Reference [10] proposed a method to optimize well locations under geological uncertainties based on response surfaces and experimental design. Reference [11] presented application of stochastic search techniques to the production scheduling of a group of linked oil and gas fields with the goal of maximizing total net present value. A genetic algorithm using problem-specific crossover operators was particularly successful in this regard. Reference [12] developed a hybrid binary genetic algorithm to optimize the placement of vertical or horizontal wells in a real faulted reservoir. A methodology to optimize the number and location of producer well in new fields was developed by [13]. Optimization of well placement using a hybrid of the genetic algorithm that enables the evaluation of reservoir and fluid properties; well and surface equipment specifications; as well as economic parameters had been done [14]. Reference [15] optimized the placement of vertical wells using a genetic algorithm without any hybridization. Reference [16] applied a binary genetic algorithm to optimize well type, location and trajectory for unconventional wells.

Reference [17] presented a technological survey of real time production optimization of offshore oil and gas production systems. Reference [18] applied genetic algorithms to scheduling and optimization of fuel oil and

International Journal of Applied Science and Mathematics
Volume 3, Issue 1, ISSN (Online): 2394-2894

asphalt section in a petroleum refinery. Two genetic algorithm models were developed to establish the sequence and size of all production shares. A special mutation operator was proposed to minimize the number of changes in the production while multi-objective fitness evaluation technique was incorporated to the genetic algorithm models. Reference[19] proposed a comparative study of three different bio-inspired optimization methodologies applied to the optimization of a Steel Catenary Riser (SCR) for floating oil production systems. Reference[20] investigated reservoir production optimization using genetic algorithms and artificial neural networks. Different optimization schemes were developed to perform production optimization on oil reservoir simulator models. Reference[21] proposed a methodology to optimize the number and placement of wells in a field through two optimization stages. Reference [22] implemented an optimization tool based on GA to optimize the number, location and trajectory of a number of deviated producer and injector wells.

Reference[23] proposed an optimization strategy based on neural networks and genetic algorithms to calculate the optimal values of gas injection rate and oil rate for oil production system. Two cases analyzed were single well production system and production system composed by two gas-lifted wells. For both cases, an objective function was maximized to reduce production cost. The determination of optimal well locations is a challenging problem in oil production since it depends on geological and fluid properties as well as on economic parameters [24]. Reference [25] addressed well placement optimization for water injection wells. Reference [26] presented optimization of multilateral well design and location in a real field using a continuous genetic algorithm. Reference [27] proposed a hybrid optimized artificial intelligent model to forecast crude oil using genetic algorithm. Optimization of injection rate and injection time for surfactant and water flooding in oil fields was investigated by [28]. Comparison of oil recovery of both surfactant and water flooding in reservoirs with various conditions was executed. Application of hybrid techniques with improved algorithm configuration to optimize steam/solvent injection methods had been examined [29]. Reference [30] presented application of a hybrid system of genetic algorithm and fuzzy logic as optimization techniques for improving oil recovery in sandstone reservoirs in Iraq. Reference[31] presented a conceptual paper on intelligent model framework for handling effects of uncertainty events for crude oil price projection.

II. Approach

The models used were nonlinear, iterative and with a very rough surface. Hybrid genetic algorithm was used for the optimization and to search the feasible region while a local optimizer, sequential quadratic programming (SQP) was used to locate precisely the optimum point. The production system model was developed in MATLAB environment and its optimization toolbox was used for the task. The decision variables used were separator pressure, flow line diameter, choke diameter and well diameter. The objective function was daily oil flow rate. Population size of twenty was used. The algorithm starts with an initial random population and the system models were solved using the hybrid function with case study obtained from previous work of [32]. After convergence was reached, optimum oil flow rate with corresponding decision variables were obtained. Optimization was run for two, three and four parameters respectively.

III. Mathematical Model Development

The model development consists of three parts: well tubing, choke and flowline.

A. Well Tubing Modeling

A two-phase model is required to model the flow characteristics of oil and gas through a vertical well. For this workBeggs and Brill's correlations were used [33]. For each step of the pressure traverse down the tube, the correlations provide flow regime, liquid hold up and pressure drop. The procedure is initiated for a given flow rate, temperature and pressure at the well head and then pressure at a given depth is calculated using the following procedures known as pressure traverse calculations [33]:

1) Based on known pressure $p_1$at location L_1, length increment ΔL is selected.
2) A pressure increment, Δp corresponding to the length increment, ΔL is estimated.
3) Average temperature and pressure in the increment are calculated.
4) Fluid properties are computed at the conditions of average temperature and pressure.
5) Beggs and Brill Correlations [33] are used to compute the pressure gradient, dp/dL in the increment at average conditions of pressure, temperature, and pipe inclination.
6) The pressure increment, $\Delta p = \Delta L(dp/dL)$ corresponding to the selected length increment is computed.
7) The values of Δp computed in steps 2 and 6 are compared. When these are not sufficiently close, a new pressure increment is estimated and steps 3 and 7 are repeateduntil the estimated and calculated values are sufficiently close.
8) Then$L = L_1 + \sum \Delta L$ and $p = p_1 + \sum \Delta p$ are set.
9) If $\sum \Delta L$ is less than the total conduit length, the procedure is repeated from step 2.

The modelling equations for well tubing including pressure gradient equations; Beggs and Brill's correlations for pressure gradient, friction factor computation and fluid property correlations can be found in detail in [33].

The total pressure gradient across a pipe section is given by the summation of pressure drops due to elevation, friction and acceleration. Thus,

$$\frac{dp}{dL} = \left(\frac{dp}{dL}\right)_{el} + \left(\frac{dp}{dL}\right)_{f} + \left(\frac{dp}{dL}\right)_{acc} \qquad (1)$$

where the elevation change component is

$$\left(\frac{dp}{dL}\right)_{el} = \frac{g}{g_c}\rho_s sin\emptyset \qquad (2)$$

The friction component is

$$\left(\frac{dp}{dL}\right)_f = \frac{(f\rho v^2)_f}{2g_c d} \quad (3)$$

and the acceleration component is

$$\left(\frac{dp}{dL}\right)_{acc} = \frac{(\rho v dv)_k}{g_c dL} \quad (4)$$

Substituting (2), (3) and (4) into (1) we have

$$\frac{dp}{dL} = \frac{g}{g_c}\rho_s sin\emptyset + \frac{(f\rho v^2)_f}{2g_c \mathrm{d}} + \frac{(\rho v \mathrm{d}v)_k}{g_c dL} \quad (5)$$

where ρ is fluid density, g is gravitational acceleration, g_c is conversion factor, $\emptyset$ is angle of elevation, v is fluid velocity, f is frictional factor and d, the pipe internal diameter. Any consistent set of units can be used in association with the above equations.

B. Fluid Property Correlations

Correlations were used for estimating fluid properties, these include: gas compressibility factor (Z) which was determined using Brill and Begg's correlations modified by Standing; solution gas oil ratio (R_s) determined using Standing correlation; oil formation volume factor (B_o) calculated from Vasquez and Beggs correlations; oil viscosity (μ_o) from Beggs and Robinson correlations, and gas viscosity (μ_g) from Lee correlations [33].

C. Choke Model

Chokes are positioned between the top of the tubing and separator to protect reservoir and surface equipment from pressure fluctuations and to maintain a stable flow among other benefits [34]. Surface chokes can operate in two distinct flow regimes: critical and subcritical flow. In critical regime, the fluid flow is a function of only the upstream pressure. Many correlations have been developed for choke which mostly are for single phase or assumed a critical regime. A multiphase model capable of modelling both critical and subcritical flow regime is used [33].

The equation for flow rate in both critical and subcritical regime is given in field units as:

$$q_L = \frac{0.525C_d d^2}{CM_2}\left\{P_1\rho_{m_2}\left[\frac{(1-X_1)(1-y)}{\rho_{L1}} + \frac{X_1 k(1-y^{k-1/k})}{\rho_{g1}(k-1)}\right]\right\}^{0.5} \quad (6)$$

where q_L is liquid flow rate in STB/day, d is choke inside diameter in inches, P_1 is upstream pressure in psia, ρ_{L1} is liquid density at P_1, T_1 in Ibm/ft^3 and $X_1$is quality (ratio of gas mass flow rate to the total mass flow rate) at P_1, T_1. CM_2 and ρ_{m_2} are constants to be determined based on the fluid properties while C_d is a discharge coefficient.k is ratio of specific heats for gas (C_p/C_v) and y is the ratio of upstream and downstream pressures.

D. Flowline Model

Beggs and Brills correlations stated in Section A is applied for any type of pipe inclination, vertical, horizontal or inclined. Here, the flowline was assumed horizontal with zero inclination angle and modelled using the Beggs and Brills correlations [33].

IV. Optimization Techniques

The optimization techniques used in this work are briefly described in this section. SQP was used jointly with GA to enhance its (GA) efficiency and to prevent it from sticking to a local optimum.

A. Sequential Quadratic Programming

A sequence of quadratic programming approximations to a nonlinear programming problem is solved by sequential quadratic programming (SQP) methods. A quadratic objective function with linear constraints made up a quadratic program. The linear constraints in SQP are usually linearizations of the actual constraints about a selected point. The objective is a quadratic approximation to the Lagrangian function, and the problem is solved by Newton's method applied to the Kuhn-Tucker conditions (KTC) of the problem.

To show the solution by SQP, consider a general nonlinear programming problem (NLP) presented as [35]

$$\min_{\boldsymbol{x}} \boldsymbol{f}(\boldsymbol{x})$$
$$such\ that: \quad \boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{b}$$
$$\boldsymbol{I} \le \boldsymbol{x} \le \boldsymbol{u}$$

where $\boldsymbol{f}$ and $\boldsymbol{g}$ are objective and equality constraint functions respectively. $\boldsymbol{I}$ and $\boldsymbol{u}$ are respective lower and upper bounds of the inequality constraints while $\boldsymbol{x}$ is a vector of decision variables. The QP subproblem can be shown to reduce to

$$Minimize: \quad \nabla\boldsymbol{L}^T\Delta\boldsymbol{x} + \frac{1}{2}\Delta\boldsymbol{x}^T\boldsymbol{B}\Delta\boldsymbol{x}$$
$$subject\ to: \quad \nabla\boldsymbol{g}\Delta\boldsymbol{x} = -\boldsymbol{g}, \quad \boldsymbol{I} \le \bar{\boldsymbol{x}} + \Delta\boldsymbol{x} \le \boldsymbol{u}$$

$\boldsymbol{B}$ is a positive-definite quasi-Newton (QN) approximation while $\boldsymbol{L}$ is a Lagrangian function.

The SQP algorithm can be summarized as follows [35]:

1) Initialize: $\boldsymbol{B^0} \leftarrow \boldsymbol{I}$(or some other positive-definite matrix), $\boldsymbol{x^0} \leftarrow \boldsymbol{x}$which is provided by the user at $k \leftarrow 0$.
2) QP sub problem is solved which yields a solution of $\Delta\boldsymbol{x}^k$ together with Lagrange multiplier estimates.
3) The termination criteria which include KTC, fractional objective change are checked and the program is stopped if any are satisfied to within the specified tolerances.
4) The penalty weights in the penalty function is updated.
5) The line search algorithm is applied to yield a positive step size.
6) The solution is updated with the new step size.
7) All functions are evaluated at the new point.
8) The step k is replaced by $k + 1$ and the procedure is restarted with step 2.

B. Genetic Algorithms

GAs start the optimal search with a set of solutions called $P = \{x_1, x_2, x_3, \cdots\cdots x_p\}$, which is known as *population* with members, x_i called individuals. A starting population is initially created, and at the start of each iteration a population is modified by replacing one or more individuals with new solutions, which are created either by combining two individuals (*crossover*) or by changing an individual (*mutation*). The procedure is as follows [35]:

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1) An initial population is chosen, and the fitness of each individual is evaluated
2) If the crossover condition is satisfied, parent individuals are selected, crossover parameters chosen, and then crossover is performed.
3) If however, mutation condition is satisfied, then mutation points are chosen and mutation is performed.
4) The fitness evaluation of offspring is performed.
5) The population is updated.

The whole of this procedure has been reported in [36].

V. Results and Discussions

After running the optimization, there was no improvement in the value of oil flow rate after ten generations. This is shown in Figure 1 for two-variable optimization. This is also applicable to the other two cases. In the figure, the best and mean values in the fitness of the ten generations are respectively -169.49 and -169.13 stb/day. The negative sign in the fitness values arose from the fact that the optimization software (MATLAB optimization toolbox) used was designed for minimization problem. To solve a maximization problem as in our case, the negation of the actual objective function is minimized which is the same as maximization of the positive value. For the stopping generation, the fitness values of the 20 individual scan be seen to be approximately equal, indicating a satisfactory stopping point. Convergence is seen to be reached right from the 8^{th} generation when we observe the plots of the best, worst and mean scores of generations 8^{th} – 9^{th} which remain relatively equal.

For the two-variable optimization, the highest optimal oil production was obtained when tubing diameter and separator pressure were optimized. For this variables combination, the amount of oil produced has seen an increment of 2.44% by decreasing the lower bound of the separator operational pressure. The next highest amount of oil production was obtained by optimizing pipeline diameter and separator pressure. For all other combinations, the optimal oil production remained significantly the same (Table I).

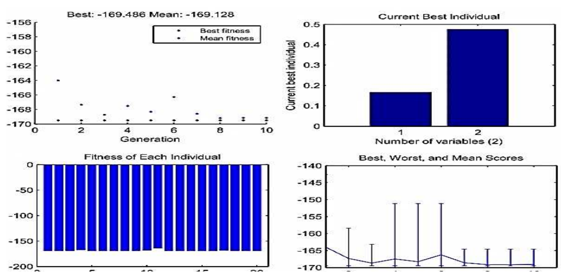

Fig. 1. GA Progress for Two-Variable Optimization

From Table II for three-variable optimization, we can see that replacing pipeline diameter with separator pressure in the optimization frame work causes a jump in the optimal oil production of 16.24%. This indicates the high sensitivity of separator pressure to the amount of oil production. Three different runs of the optimization was performed with the three diameters as decision variables while maintaining the boundaries. For each run, a slightly different optimal variables combination was obtained but with the same optimal oil rate. This is due to stochastic nature of GA, it is possible to obtain different solutions for every optimization run, but almost equal objective function is obtainable as long as the simulation is allowed to reach convergence.

Table III shows the optimization with all the four variables. As in the previous cases, the most sensitive parameter found is separator pressure. Here, changing the pressure bounds as well as those of the tubing diameter, caused an increase in the optimal oil production of 1.11%.Changing the boundaries of the other variables has not shown any appreciable change in the amount of oil production.

It can be deduced generally from the results presented in Tables I-III that the optimum pipeline size sticks to upper search interval while separator pressure sticks to lower boundary. This is in line with literature theory that as the pipe line diameter increases the frictional losses decreases [32]. So, increase in horizontal pipeline diameter will continue to reduce the frictional losses. Also, a lower separator pressure favors the quantity of oil produced.

Table 1. Case 1 for Two-Variable Optimization

Variables		Interval		Optimum Values		Optimized Rate
1	2	1	2	1	2	(STB/D)
d_p (in)	d_{wc} (1/64”)	[1,2]	[10,60]	2	20.77	169.49
		[1,2]	[10,40]	2	30.46	169.49
	d_t (in)	[1,2]	[1,3]	2	2.30	169.64
		[1,2]	[1,3]	2	2.30	169.64
	P_{sp} (psia)	[1,2]	[30,70]	2	30	198.69
d_{wc} (1/64”)	d_t (in)	[12,50]	[1,3]	15.55	2.30	169.64
		[12,50]	[1,3]	17.40	2.30	169.64
d_t (in)	P_{sp} (psia)	[1,3]	[30,60]	2.37	30	198.72
		[1,3]	[14.7,114.]	2.39	14.7	203.68

Table 2. Case 2 for Three-Variable Optimization

Variables			Interval			Optimum Values			Optimized Rate
1	2	3	1	2	3	1	2	3	(STB/D)
d_t (in)	d_{wc} (1/64”)	d_p (in)	[1,3]	[15,50]	[1,5]	2.30	47.15	5	171.99
			[1,3]	[15,50]	[1,5]	2.30	28.35	5	171.99
			[1,3]	[15,50]	[1,5]	2.30	28.69	5	171.99
	d_p (in)	P_{sp} (psia)	[1,2]	[1,3]	[20,40]	2.00	3.00	20	205.33

Table 3. Case 3 for Four-Variable Optimization

Interval				Optimum Values				Optimized Rate (STB/D)
d_t (in)	d_{wc} (1/64”)	d_p (in)	P_{sp} (psia)	d_t (in)	d_{wc} (1/64”)	d_p (in)	P_{sp} (psia)	
[0.5,3]	[15,50]	[1,5]	[20,70]	2.40	16.02	5.00	20.00	207.97
[1,3]	[15,50]	[1,5]	[15,95]	2.412	47.01	5.00	15.00	210.30
[1.5,2.5]	[20,80]	[2,4]	[15,55]	2.412	21.31	4	15.00	210.17
[1.5,2.5]	[20,120]	[2,4]	[15,55]	2.412	41.93	5.00	15.00	210.17
[1.5,2.5]	[20,120]	[2,4]	[15,55]	2.412	110.12	5.00	15.00	210.17

It can also be inferred that a maximum tubing diameter exists for an optimum oil rate. Any increase beyond the maximum point will not only lower the oil rate but could render the flow unstable (Tables I - III).

It can be observed that the search interval affects the optimum choke size. For any run made, a separate choke size is obtained keeping the optimum rate unchanged.

VI. Conclusion and Recommendation

Optimization of petroleum production system was carried out using hybrid genetic algorithm. The algorithm was found to be efficient in determining optimal values for key components of the system which include tubing diameters for well and flowline, choke size and separator pressure. It was found that a maximum tubing diameter exists for an optimum oil flow rate and stable flow. For choke size determination, the optimum value is affected bychosen search interval. It was also found that separator pressure is the most sensitive variable to oil production rate.

Although same optimum flow rate was obtained for different choke sizes, the flow pattern may be different. This can be an opportunity for integrating this study with flow assurance

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