



Petroleum Research

Petroleum Research 2018 (August-September), Vol. 28, No. 99. 45-50

DOI: 10.22078/pr.2018.2475.2146

Multi-objective Optimization using Integration of Experimental Design Methods, Particle Swarm Optimization, and Fuzzy Logic, Case Study: Polymer Injection for Enhanced Oil Recovery

Mohammad Saber Karambeigi

IOR Research Institute, Tehran, Iran

ms.karambeigi@nioc.ir

DOI: 10.22078/pr.2018.3092.2426

Received: January/02/2018

Accepted: March/18/2018

Abstract

Single-criterion techniques in which just a single objective is considered cannot offer the perfect solution because they cannot take into account the trade-off between conflicting technical and economic conditions. In this study, a multi-criteria algorithm was developed based on experimental design methods, particle swarm optimization, and fuzzy logic. It was able to solve the optimization problem via considering different objectives simultaneously, finding the optimum values of effective factors. To evaluate the efficiency of the workflow, a case study was done in which influential parameters (water flooding duration, polymer concentration, duration of polymer injection, and polymer adsorption) for the design of an enhanced oil recovery operation of polymer flooding in a sandstone reservoir were optimized considering technical (cumulative oil production) and economic (net present value) objectives. The results were compared to the results of the base-case scenario as well as a single objective algorithm (particle swarm optimization). Compared to the base-case scenario, cumulative oil production increased more than 58% and net present value rose from \$ 6.9 to 13.1 MM as well. Although the optimum scenario proposed by single-criterion optimization algorithm based on technical objective produced more oil compared to the best solution of the multi-purpose algorithm, a severe reduction was observed in the economic objective simultaneously. Finally, the results of this study demonstrate that multi-objective algorithms are more applicable to precise and realistic decision-making.

Keywords: Polymer Flooding, Multi-objective Optimization, Particle Swarm Optimization, Fuzzy Logic, Chemical Enhanced Oil Recovery.

INTRODUCTION

Nowadays, the efficiency of primary and secondary mechanisms for producing oil reaches up to 50%; in addition, an immense amount of oil remains intact in the reservoir which is a suitable goal for enhanced oil recovery (EOR) processes [1]. EOR methods can be categorized into four main groups: thermal, solvent, chemical, and other techniques [2].

Polymers are the most applicable chemicals used in chemical EOR (CEOR) approaches. They help the enhancement of oil recovery via different mechanisms such as the improvement of macroscopic sweep efficiency and plugging of high permeable zones [3].

Outstanding performance of polymers has been proved in a wide range of experimental and simulation studies. However, successful application of polymer flooding depends on the detection, control and optimization of influential parameters because the efficacy of the process is threatened by some restrictions such as complexity of the CEOR process, harsh conditions of the reservoirs (high temperature and high salinity), polymer price, and environmental considerations [4]. To optimize this process, different methodologies have been proposed such as simulation-based approaches [5], sensitivity of effective parameters [6], surrogate-based optimization

[7], and experimental design [8]. Almost, a single objective (e.g. technical indexes) has been considered in aforementioned approaches. In this case, field projects are implemented in high risk atmosphere. Useful optimization of polymer injection is done when different objectives are considered at the same time. In other words, multi-objective optimization methods have higher priorities than single-attribute ones. A Multi-purpose optimization approach defines as a methodology by which the trade-off between conflicting objectives can be handled. Moreover, limited studies are available in the literature in which such approaches have been developed to optimize the relevant processes. For example, a multi-objective optimization approach based on Pareto optimization algorithm has been presented by Ekkawong et al [9]. In this paper, a hybrid workflow composed of experimental design, particle swarm optimization, and fuzzy logic methodologies is proposed to optimize polymer flooding in terms of technical and economic objectives.

METHODOLOGY

Four input parameters were as follows: the period of water flooding, polymer concentration, the period of polymer injection, and polymer adsorption. The range of influential parameters is presented in Table 1.

Table 1: Effective parameters in the polymer injection process.

Variable	Unit	Level -a(Lower Limit)	Level -1	Level 0	Level 1	Level +a(Upper Limit)
Waterflooding Period	Day	0.875	61	153.5	246	306.125
Polymer concentration	%wt	0.01875	0.1	0.225	0.35	0.43125
Polymer Injection Time	Day	3.75	150	375	600	746.25
Polymer Adsorption	-	0.025	1	2.5	4	4.975

Moreover, cumulative oil production and net present value (NPV) were considered as the responses of the process. In the first stage of the hybrid workflow, statistical modeling was done using design of experiments (historical data method). For this purpose, 30 runs were designed, each of which contained a combination of inputs. Thereafter, cumulative oil production and net present value were calculated using UTCHEM simulator and economic calculation based on \$50 as the price of oil respectively [10].

Corresponding responses were then fed into Design Expert software and different models were fitted to the data, finding the best relationships between inputs and outputs in terms of mathematical equations to be used as fitness functions in the stage of production. In the second stage, a multi-objective optimization method was employed. To this end, 25 particles in a population were placed in the sampling space according to their random position and velocity characteristics. Then, fitness functions were applied to calculate the fitness value of each particle technically and economically. These equations cannot be used to calculate pbest (the best position of each particle) and gbest (the best position of the population) because both objectives must be considered simultaneously. For this purpose, fuzzy logic was coupled with particle swarm optimization by which two objective functions are combined to produce a unique objective function. First, fuzzification was implemented on the fitness functions and fuzzy equations were produced according to Eq. 1:

$$\mu_f(F_k) = \begin{cases} 0 & F_k < F_k^{\min} \\ \frac{F_k - F_k^{\min}}{F_k^{\max} - F_k^{\min}} & F_k^{\min} < F_k < F_k^{\max} \\ 1 & F_k > F_k^{\max} \end{cases} \quad (1)$$

In which k stands for indexes (1 for technical and 2 for economic indexes), F_k is the corresponding response to k^{th} index, and F_k^{\max} and F_k^{\min} are the maximum and minimum values of fitness functions, respectively. The ζ_i as satisfaction (unique or Zeta) function was then produced when the minimum fuzzy function was taken into account:

$$\zeta_i = \min \{ \mu_f(F_1), \mu_f(F_2) \}_i \quad (2)$$

Here, the optimization algorithm tried to maximize ζ_i . The function value reached unity, and consequently, fuzzy objective functions improved. In such conditions, $pbest_i$ was calculated for each particle, and gbest of the population was calculated accordingly:

$$gbest = \text{Max} \{ pbest_i \} \quad (3)$$

Next, the position and velocity of the particles were updated, and they were placed in the new population. The values of pbest and gbest were updated if required, and finally the last gbest was the solution of the multi-objective problem.

CASE STUDY

It was an undersaturated (initial pressure of 1800 psi) sandstone reservoir with the dimensions of 720 ft × 720 ft. The reservoir was a heavy oil type with 2 MM bbl of original oil in place. It has passed a short period of water flooding in early production stage, and consequently polymer flooding has been started. Injection pattern was 5-spot. Moreover, injection rate was 375 bbl/day, and production scenario was constant pressure of 1300 psi. Further information can be found in Table 2.

RESULTS AND DISCUSSION

In this paper, CEOR method of polymer flooding was optimized using a multi-attribute optimization algorithm.

Table 2: General properties of reservoir model.

Variable	Unit	Value
Cells in x, y and z directions	-	15, 15 and 36
Grid-block size in X and Y directions	ft	32.8-131.2
Grid-block size in Z direction	ft	2.23-5.68
Initial water saturation	%	4
Permeability	mD	200-17000
End point of water relative permeability	-	0.6
End point of oil relative permeability	-	0.93
Power of relative permeability curve for water phase	-	2.5
Power of relative permeability curve for oil phase	-	4-8
Reservoir temperature	°C	62
Water viscosity in reservoir conditions	cp	0.48
Oil viscosity in reservoir conditions	cp	17

The first stage of the hybrid workflow was statistical modeling to find objective functions. The best equations were quadratic types for both responses. In addition, the analysis of variance (ANOVA) is presented in Table 3. It demonstrates that fitted models were significant in confidence limit of 99.9 % because $\text{prob}>F$ of two models were less than 0.0001. Moreover, R^2 (R-squared), R_{adj}^2 (adjusted R-squared) and R_{pred}^2 (predicted R-squared) were next to the unity. Other parameters of ANOVA table were favorable for both responses. Therefore, developed second-order equations could be used as the objective functions.

In the next stage of the workflow, particle swarm optimization and fuzzy logic were coupled to develop a multi-purpose optimization approach.

In the first population, 30 particles were placed

randomly in the sampling area. It should be noted that three inputs varied between their lower and upper limits (Table 1) while polymer concentration as the last factor was set to a constant value (value 2) because each polymer has its own concentration in a determined reservoir. Using objective functions (calculated in the previous stage) as well as Equations 1 to 3, fitness functions of each particle were determined, and thereafter, p_{best} and g_{best} values were calculated. In the next population, position of the particles was updated, and new values of p_{best} and g_{best} were then determined. The algorithm progressed until it reached the stopping criterion which was 60 populations. The trend of satisfaction function is demonstrated in Figure 1.

Table 3: Analysis of variance for fitted equations.

Parameter	Model 1 for cumulative oil production	Model 2 for net present value
Model F value	160.02	129.82
Model $\text{prob}>F$	< 0.0001	< 0.0001
R-squared	0.9933	0.9918
Adjusted R-squared	0.9871	0.9842
Predicted R-squared	0.9659	0.9579
CV%	2.39	3.77
Adequate precision	43.175	42.071

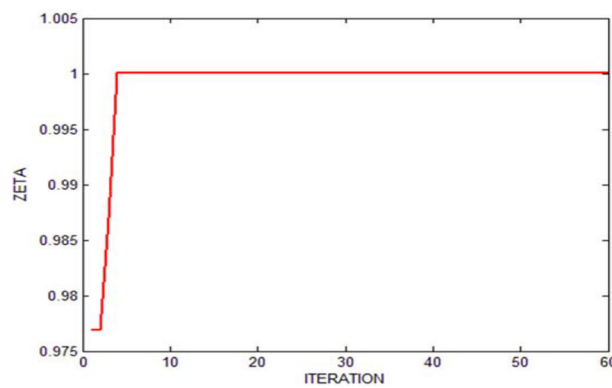


Figure 1. The trend of the variation of satisfactory (Zeta) function.

The parameter of gbest of the 60th population was the solution of the problem. Figure 2 shows how two responses were optimized while algorithm went from population 1 to 60.

The best (optimum) scenario was as follows: water flooding should be done for 68 days before the start of polymer injection. Then, a polymer slug (adsorption of 2) with the concentration of 0.34 %wt. should be injected for 671 days. In this case, cumulative oil production has been increased from 426100 (in base-case scenario) to

675812 bbl while NPV has been improved from 6.9 to \$13.1 MM.

Comparing this multi-objective algorithm with a simple-objective particle swarm optimization revealed that when just the technical objective was considered cumulative oil production increased 1825 bbl while NPV decreased \$1.6 MM. Therefore, successful plans of operation must take into account all conflicting objectives rather than a single goal.

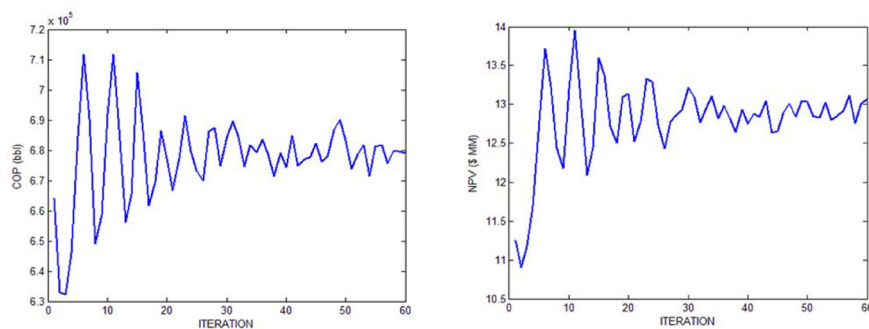


Figure 2: The progress trends of the objectives (left: cumulative oil production and right: NPV).

CONCLUSION

According to the results of this paper, the following conclusions can be drawn:

1- In this paper, a multi-objective optimization methodology was developed which was composed of two main stages: the former was the statistical modeling to find objective functions

using design of experiments and the latter was a hybrid optimization approach in which fuzzy logic and particle swarm algorithm were coupled.

2- In the modeling stage, historical data (as the method of the design of experiments) demonstrated favorable results because developed R-squared, adjusted R-squared, and

predicted R- squared were more than 0.99, 0.98 and 0.95 respectively.

3- By considering technical and economic objectives simultaneously, hybrid workflow provided a multi-attribute solution. The optimum scenario boosted oil production from 426100 to 675812 bbl while net present value increased \$6.2 MM.

REFERENCES

- [1]. Muggerridge A., Cockin A., Webb K., Frampton H., Collins I., Moulds T. and Salino P., "Recovery rates, enhanced oil recovery and technological limits," Philosophical Transactions, Series A, Mathematical, Physical, and Engineering Sciences, pp. 372, pp.1-25, 2014.
- [2]. Lake L. W., Johns R., Rossen B. and Pope G., "Fundamentals of enhanced oil recovery," ed., Society of Petroleum Engineers, pp. 496, 2014.
- [3]. Sheng J. J., Leonhardt B. and Azri N., "Status of polymer-flooding technology," Journal of Canadian Petroleum Technology, Vol. 54, pp. 116-126, 2015.
- [4]. Stoll W. M., Al Shureqi H., Finol J., Al-Harthy S. A. A., Oyemade S., De Kruijff A., Van Wunnik J., Arkesteijn F., Bouwmeester R. and Faber M. J., "Alkaline/surfactant/polymer flood: From the laboratory to the field," SPE Reservoir Evaluation and Engineering, Vol. 14, pp. 702-712, 2011.
- [5]. AlSofi A. M. and Blunt M. J., "Polymer flooding design and optimization under economic uncertainty," Journal of Petroleum Science and Engineering, Vol. 124, pp. 46-59, 2014.
- [6]. Anderson G. A., Delshad M., King C. B., Mohammadi H. and Pope G. A., "Optimization of chemical flooding in a mixed-wet dolomite reservoir," SPE Paper 100082, Presented at SPE/DOE Symposium on Improved Oil Recovery, Tulsa, Oklahoma, April 22-26, 2006.
- [7]. Zerpa L. E., Queipo N. V., Pintos S. and Salager J. L., "An optimization methodology of alkaline-surfactant-polymer flooding processes using field scale numerical simulation and multiple surrogates," Journal of Petroleum Science and Engineering, Vol. 47, pp. 197-208, 2005.
- [8]. Prasanphanich J., Kalaei M. H., Delshad M. and Sepehrnoori K., "Chemical flooding optimisation using the experimental design approach and response surface methodology," International Journal of Oil, Gas and Coal Technology, Vol. 5, pp. 368-384, 2012.
- [9]. Ekkawong P., Han J., Olalotiti-Lawal F. and Datta-Gupta A., "Multiobjective design and optimization of polymer flood performance," Journal of Petroleum Science and Engineering, Vol. 153, pp. 47-58, 2017.
- [10]. Sangvaree T., "Chemical flooding optimization using the experimental design and response surface method," M.Sc. Thesis, Department of Petroleum and Geosystems Engineering, The University of Texas at Austin, pp, 2008.