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Economic Development of Shale Gas Reservoirs via Optimal Design of Hydraulic Fracture Stages: An Efficient Evolutionary Multi-Objective Approach

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Summary

Recently, due to a rapid decline in petroleum prices the industry experiences higher demand for fast optimization strategies in unconventional reservoir management to keep the projects profitable and produce commercial volumes of natural gas from shale plays. To achieve these objectives we propose to couple shale gas numerical reservoir simulation with advanced optimization techniques for optimal hydraulic fracture design and placement. Judicious application of this approach can yield higher shale gas reserve estimates and improved project revenue. In this paper we present our novel multi-objective evolutionary optimization framework that allows to place hydraulic fractures in presence of multiple economic and/or production objectives.

Our workflow has an evolutionary-based optimization engine that efficiently explores a multi-dimensional solution space and assesses the “goodness” of each arrangement of hydraulic fractures and their parameters (such as half-length) based on values of multiple objectives. These objectives can be conflicting (improvement in one inevitably leads to decline in another) or non-conflicting (both objectives increase or decrease simultaneously). Our implementation the multi-objective genetic algorithm handles both scenarios and provides the engineer with the set of optimal solutions (the Pareto optimal set). Our novel multi-objective evolutionary optimization approach to hydraulic fracture placement is unparalleled in its flexibility. All parts of the objectives and economic parameters are fully customizable for fit the needs of a specific operator of unconventional assets.

Introduction

Efficient optimization approaches to management of unconventional gas resources (including shale and tight gas reservoirs) has gained much attention in the industry and academia in the last decade (Rahman and Sarma, 2011; Carpenter, 2013; Barree et al., 2015). This study is one of the first attempts to explore applicability and benefits of MOO to improve commercial success of unconventional gas reservoirs. First, we introduce the key concepts of MOO, discuss its advantages in comparison to single objective optimization, comment on its applicability to the proposed problem, and present the workflow of an MOO algorithm, the Improved Non-dominated Sorting Genetic Algorithm (NSGA-II). Second, we describe and specify our shale gas simulation model that is used for generating production data and evaluation of the objectives. Third, we discuss two possible MOO scenarios, specifically, optimization with two conflicting objectives and optimization with two non-competing objectives. Last, we present the results of our numerical experiments and draw conclusions about benefits of our MOO approach for future field applications.

Theory and Method

Application of MOO to the problems in commercial reservoir management gives the operators explicit means of evaluating their development options in presence of several objectives (Konak et al., 2005). To be more specific, small operating firms might aim at high short-term revenue (or high initial production rates) and low water production, because after several years these companies might want to re-sell the field and start producing new assets. In contrast, large integrated operators might buy already producing fields, develop long-term exploitation strategies, and consider if certain production scenarios meet their expectations in the long term. To help decision makers from both types of operators, we propose our novel approach to practical handling of several conflicting or non-competing objectives in unconventional gas development. Our MOO approach gives the user (or the operator) a procedure to decide which trade-off development strategy to choose and what economic implications of such choice would be.

A typical MOO problem with n objectives can be written mathematically as follows:

$$\max/\min f = J(u) = [J_1(\bar{u}), J_2(\bar{u}), \ldots, J_n(\bar{u})], \quad (1)$$

such that the optimized multi-dimensional function f belongs to the space of objective functions O, $f=(J_1,J_2,\ldots,J_n)\in O$ and the multi-dimensional control vector u belongs to the space of parameters U, $u=(u_1,u_2,\ldots,u_m)\in U$ (Zitzler and Thiele, 1999). **Fig. 1** schematically demostrates the results of maximization with two objectives (J_1 and J_2) mapped onto two-dimensional space O. The figure also provides an interpretation in red of the Pareto front of optimal solutions (Rank 1 solutions) and the ranking of the dominated solutions in the optimization problem from **Eq. 1** (Zitzler and Thiele, 1999). The Pareto optimal front is defined as a set of solutions or multi-dimensional points in the space O that are not dominated by any other point in this space (Sreekanth et al., 2012).

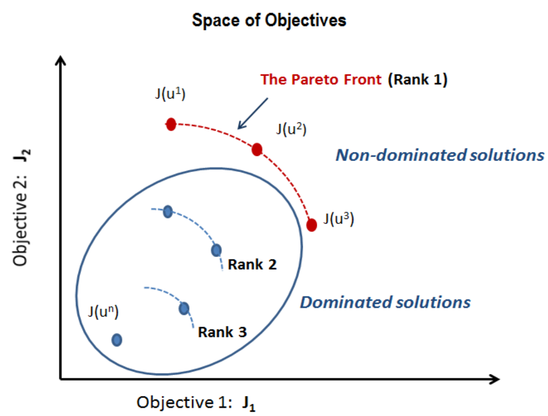


Figure 1. The two-dimensional space of objectives O (objective functions J_1 and J_2) with the Pareto optimal front of non-dominated solutions and dominated solutions of lower ranks.

The parameter space U contains multi-dimensional binary vectors that encode locations and half-length of HF stages (**Fig. 2**). To map these binary vectors of control variables to the space of objectives O, we use NSGA-II which is a multi-objective modification of a genetic algorithm. NSGA-II has been developed to handle multiple conflicting or non-competing objectives. It combines typical genetic operators such as crossover, elitism, and mutation with non-dominated sorting of the population of control vectors to achieve fast evolution toward the Pareto optimal set (Deb et al., 2002).

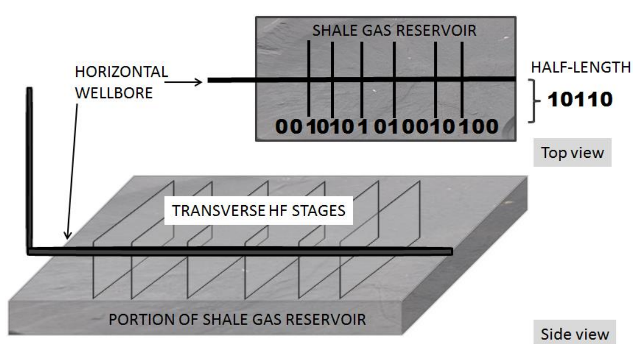


Figure 2. Schematic representation of a shale reservoir with one horizontal wellbore and six transverse HF stages and translation of HF locations and half-length into a binary control vector.

The choice of NSGA-II for optimal HF stage placement is not accidental and is motivated by several benefits of this MOO algorithm. One of the biggest advantages of NSGA-II is that it does not require assignment of weights to each objective. Unlike once popular aggregate function approach that requires time-consuming evaluation of various weights, NSGA-II constructs the multi-dimensional space of objectives O and finds non-dominated (or optimal) solutions belonging to the Pareto front (Das and Dennis, 1997). Another reason that makes NSGA-II particularly attractive for our problem is that NSGA-II is computationally efficient and requires minimal number of evaluations of the objectives (which involve time-consuming numerical simulator calls).

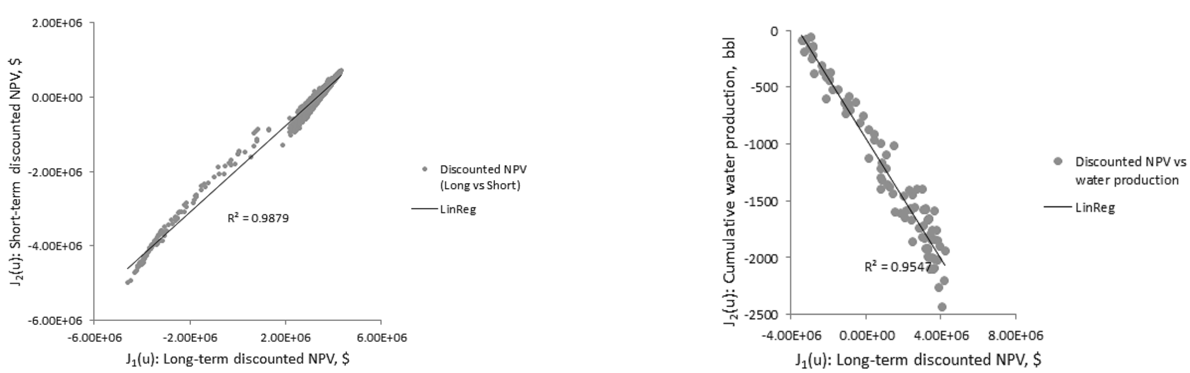
Examples

For the purposes of demonstrating the capabilities of our MOO framework, we offer test scenarios with two objectives that are competing and non-competing. One of the most common objectives in unconventional gas industry is discounted NPV, which can be formulated in various ways depending on short- and long-term goals of the gas operator. One of the most popular expressions of discounted NPV has several key parameters, namely, the discount factor, market or wellhead price of gas or petroleum fluid, operational and capital expenditures, etc. These parameters are organized into the following expression (**Eq. 2**) that contains discounted revenue in the first term and all expenditures in the second one:

$$DNPV = \sum_{k=1}^{K} \frac{\left(Q_g{}^k \cdot r_g - Q_w{}^k \cdot r_w - O\right) \cdot \Delta t^k}{(1+b)^{t^k/365}} - \left(C_w + N_{HF}\left(C_{fb} + C_{fl} x_{length}\right) + L_w C_p\right). \quad (2)$$

In **Eq. 2**, k is defined as a time period index, K corresponds to the total number of production periods simulated [days], $Q_g{}^k$ contains gas production rate during production time period k [mscf/day], r_g is wellhead gas price [$/mscf], $Q_w{}^k$ gives water production rate during production time period k [bbl/day], r_w is estimated cost of proper water disposal [$/bbl], O is typical operational expenditure of the horizontal well per day [$/day], Δt^k is duration of the *k*th production time period [days], b is a surveyed from literature discount factor [%/year], C_w is base cost of drilling the vertical part of the producing well [$], N_{HF} is the number of transverse HF stages along the wellbore of interest, C_{fb} is typical base cost of hydraulic fracturing per stage [$], C_{fl} is the cost of HF stage per unit of length [$/ft], x_{length} is length of HF stage [ft], L_w is horizontal portion of the producer in grid blocks, and C_p is well penetration cost per grid block [$].

Fig. 3 provides data generated by the two possible MOO scenarios: (a) is non-competing objectives of short- and long-term discounted NPVs and (b) is conflicting objective of long-term discounted NPV and cumulative water production. In the case (a) the objectives do not conflict and, therefore, exhibit a positive correlation between values of each objective (positive slope with high R^2). Improvement in one objective inevitably leads to improvement in another. **Fig. 3(a)** provides scatter plot of short- and long-term (1 and 5 years) discounted NPVs. **Fig. 3(b)** presents another scenario that is of great interest to the industrial users: two conflicting objectives.



(a) **(b)**

Figure 3. Two MOO scenarios with (a) non-competing objectives and (b) conflicting objectives.

Conclusions

In this study we proposed, formulated, implemented, and tested an MOO algorithm NSGA-II and successfully applied it to the problem of optimal HF stage placement. We showed that multiple objectives can be economic (short- and long-term discounted NPVs) or production (cumulative water production) and they integrate well into the MOO framework. Our implementation handles objectives efficiently and produces the Pareto optimal front without requiring the user to assign weights to each objective.

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