Fuel 206 (2017) 467–481

Contents lists available at ScienceDirect

Fuel

journal homepage: www.elsevier.com/locate/fuel

Full Length Article

A robust proxy for production well placement optimization problems

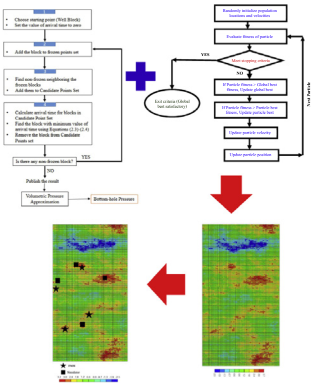
Behzad Pouladi[a], Sahar Keshavarz[a], Mohammad Sharifi[a,*], Mohammad Ali Ahmadi[b]

[a] Department of Petroleum Engineering, Amirkabir University of Technology, Tehran, Iran
[b] Department of Petroleum Engineering, Ahwaz Faculty of Petroleum Engineering, Petroleum University of Technology, Ahwaz, Iran

HIGHLIGHTS

- Fast Marching Method (FMM) is used as a proxy to optimize production well configuration.
- The proxy employs volumetric pressure approximation provided by FMM.
- FMM captures dynamic reservoir behavior and more reliable than mathematical proxies.
- This proxy doesn't need any training prior to use and can be used independently.
- Results that are in good agreement with those provided by reservoir simulator.
- Computational cost associated with well placement problem was significantly reduced.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 1 July 2016
Received in revised form 2 June 2017
Accepted 6 June 2017

Keywords:
Fast Marching Method
Production well placement
Optimization
Proxy
Particle Swarm Optimization (PSO)

ABSTRACT

Finding optimum well locations is still among the most challenging reservoir engineering problems. Reservoir simulators are routinely used to evaluate different configuration of well locations in the reservoirs. However, simulation of giant field models is computationally demanding and time consuming. In the current study, a novel proxy with the objective function that is based on volumetric pressure approximation provided by Fast Marching Method (FMM) is introduced. This proxy calculates the wells bottom-hole pressure at the end of unsteady state period. The locations where the calculated bottom-hole pressure are maximum will likely leads to maximum Net Present Value (NPV). Foremost, The FMM-based approach is applied on the single production well placement problem and the correlation between results provided by this approach and the conventional simulator-based method is calculated. Thereafter, FMM-based approach is coupled with Particle Swarm Optimization (PSO) algorithm and applied to multiple production well placement in two standard reservoir model. Results provided by the new approach is compared with simulator-based approach in terms of performance and time efficiency. Results reveal that FMM-based approach can provide satisfactory results while significantly reducing computational cost.

1. Introduction

It has been over a decade that the international community is putting much effort to replace the fossil fuels with novel and renewable resources of energy. However, energy reports reveal

---

* Corresponding author.
E-mail address: m_sharifi@aut.ac.ir (M. Sharifi).

http://dx.doi.org/10.1016/j.fuel.2017.06.030

Nomenclature

Acronyms

FMM	Fast Marching Method
FDPs	field development plans
BHP	bottom-hole pressure
NPV	Net Present Value
Capex	capital expenses
PSO	Particle Swarm Optimization
NGB	number of grid blocks

Greek letters

μ	fluid viscosity
ϕ	porosity
τ	time of flight (arrival time)

the undeniable fact that fossil fuels, especially hydrocarbon resources are still the main and will remain the key supplier of world's energy demand for decades. This fact provides a strong motivation for development of new oil and gas fields across the world. Field development plans (FDPs) are still among the most challenging reservoir engineering problems. Well placement is a crucial step in preparing an optimum FDP. In practice, optimum well configuration is chosen by aid of geological knowledge, reservoir engineering expertise and judged by reservoir performance information acquired using a reliable reservoir model and reservoir simulators. Strictly speaking, in traditional approach, numerous well placement scenarios are prepared, scenarios are analyzed using the reservoir model and reservoir simulator and finally optimum scenario is chosen based on the information acquired in previous step. This approach entails its own set of the difficulties. First of all, it's impractical to investigate all possible well configuration scenarios. This encourages the researches to apply the intelligent computational tools (optimization algorithms) since they can provide a systematic and a general framework to find the optimum solution to the optimization problems. The second difficulty is related to evaluation of the well configuration scenarios. Due to large number of parameters, complex and nonlinear equations that predict the reservoir performance, there is no explicit equation that could be used to describe the reservoir performance and one must employ the numerical reservoir simulation in order to assess the well configuration scenario. This is normally time-consuming and requires massive computational effort especially for giant and high resolution reservoir models. There are list of measures that may help to address this problem. Computational resource enhancement is the most obvious solution which is not usually desirable and is still considered as a limiting factor due to extra costs that may impose. In another attempt, some authors have suggested reservoir models size reduction to tackle computational load. There are many publications regarding the application of upscaling in well placement optimization [1–3]. Although upscaling may alleviate the computational cost but there are still ambiguous points regarding the applicable upscaling methods. The other practical solution is to find a computationally efficient substitution for reservoir simulators. Application of proxies as an alternative to reservoir simulators has long been an interesting issue and received much attention in recent years [4–7]. Zarei et al. [8] applied the Neuro-Fuzzy proxy to determine the optimal location for production wells using the Net Present Value (NPV) as their objective function. In their presented example, they conducted 500 simulation runs prior to the beginning of the well placement optimization. They employed 400 of simulation runs to train Neuro-Fuzzy proxy and the remaining 100 simulation runs for testing the constructed proxy model in which they found their trained model capable of predicting the simulation results with satisfactory accuracy (Maximum error was less than 5%). They then applied Genetic Algorithm to find the optimal well locations using their trained proxy model. They found the Neuro-Fuzzy proxy an efficient tool for reducing the computational time and reliable as a substitution to reservoir simulators. Artus et al. [9] introduced a statistical proxy to optimize well types and locations in nonconventional reservoirs. Their proxy is based on the cluster analysis and is shown to be effective in reducing the computational time while providing an opportunity to identify the optimum scenario by considering only 10% or 20% of whole set of scenarios. Zubarev [10] presented a comprehensive study on the application of proxy modeling techniques in production forecasting, optimization and their ability to mimic reservoir simulators response. He employed three different simulation models in order to assess the effect of model structures on the performance of proxy-models. He found all proxy models strongly dependent on model complexity, quality of input data into the proxy models and dimension and complexity of design space. Wilson and Durlofski [11] proposed a reduced physic model to optimize optimal locations, lengths and number of fracture stages for a horizontal well in shale gas reservoirs. Their approach comprises of generating a reduced-physic surrogate model using a three-dimensional full physics simulator. The surrogate model was history matched to provide predications close to full physic simulation results. The surrogate model was then replaced by reservoir simulator in the course of optimization process. Their approach was tested on two examples and was shown to be efficient while speeding up the optimization process. Golzari et al. [12] suggested a new strategy for construction of surrogate models to replace with the reservoir simulators in production optimization problems. They employed a dynamic artificial neural network to estimate function values while being trained. They investigated the performance of constructed surrogate model by comparing with actual reservoir model and they concluded that their surrogate model can provide accurate reservoir performance prediction while reducing associated computational cost. Haghighat Sefat et al. [13] employed online adaptive artificial neural network, Latin hypercube sampling and an intelligent sample selection algorithm to generate a proxy model. Performance of proposed approach was compared with conventional offline artificial neural network and was found to be capable of generating fast and accurate model. In a work done by Castellini et al. [14], they utilized the thin-plate spline nonlinear regression method to build a proxy model and applied it to a field development problem. They concluded that their approach construct proxy models that excel the proxy models with traditional design.

PSO is a stochastic global optimization algorithm presented by Eberhart and Kennedy [15]. The algorithm idea originates from flocking and schooling patterns of birds and fish. The flock of birds looking for the source of the food will move in the direction of the member who is closest to the food chirps and the other birds swing around in his direction. PSO algorithm employs set of candidate solution called particles (collection of particles are called swarm) which are assigned an initial velocity at the start of algorithm implementation. Then, the objective function for each particle location is evaluated and the best location corresponding to the best objective function value is determined. Next, new velocities based on the current velocity, particles individual best locations and the neighbor's best locations are assigned to the particles. Then, it iteratively updates the particles locations until the