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A systematic integrated approach for waterflooding optimization

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ABSTRACT

In near offshore oil fields, drilling and platform construction costs are high. Therefore, waterflooding optimization becomes the cheapest and most effective method to enhance project economics and consequently receive considerable attention. In this paper, a systematic approach was proposed to automatically determine well placement and operation constraints. The well-placement was optimized through an efficient ranking-based method which consisted of two stages. In the first stage, it was assumed that every column of cell in the reservoir simulation model contained a producer. Through iterative simulation, the most effective producers were identified by applying the screening criteria to maximize the oil production. In the second stage, the injector-placement was determined based on the dynamic injection allocation and volumetric sweep efficiency of waterflooding patterns through streamline numerical simulation. This ranking-based well-placement optimization method was validated by two examples. The results suggest that this method is very efficient and effective. Also, the adjoint-based optimization algorithm was employed to optimize the water injection rate for each injector and the liquid production rate for each producer. This systematic waterflooding-optimization approach was applied to manage NP1-29 Block, a near offshore faulted reservoir in China. After the optimization, 10-year oil production increased about 16% over the conventional waterflooding design.

1. Introduction

Waterflooding optimization in near offshore oil fields is a demanding and challenging task. As such, it is important to have optimized well pattern at the very early stage of waterflooding to lessen the high cost of drilling and platform construction. Moreover, in offshore oil fields, a higher oil production rate is often necessary to reduce the payback period. However, high production and injection rates will lead to early water breakthroughs and will increase water cut, which reduces oil recovery. Therefore, optimizing well placement and operation rate is the most economical and effective method to enhance the waterflooding performance and improve oil recovery factor in near offshore oil fields.

In oil field development, optimal well placement is a critical but also a complicated decision due to a great number of geological and engineering variables involved. In the current industry practice, well placement is often determined through manual approaches, which is arduous and tedious since they rely on engineering judgments and "trial and error". In addition, manual approaches fail to account for the effect of subsurface heterogeneity on well placement when regular well patterns such as 5-spot, 7-spot, and 9-spot are applied. Manual approaches are also problematic because they only consider limited scenarios because of various reservoir uncertainties. Over the years, much research has been done to develop the automatic optimization algorithm to assist the well-placement decision-making process and avoid manual approaches. These algorithms are categorized into two groups. The first are stochastic gradient-free methods—the Simulated Annealing Algorithm (Beckner and Song, 1995), Genetic Algorithms (Montes et al., 2001; Yeten et al., 2003), Artificial Neural Networks (Centilmen et al., 1999), and Simultaneous Perturbation Stochastic Approximation (Spall, 2003) and their variants (Badru and Kabir, 2003; Ozdogan et al., 2005). The second are gradient-based methods such as the adjoint-based gradient method (Handles et al., 2007; Wang et al., 2007).

Stochastic methods are easy to apply because they typically do not require gradient information. However, they usually require hundreds or thousands of simulations, making them inefficient and perhaps not able to handle large reservoir with many wells. On the other hand, gradient-based algorithms are often seen as more efficient since convergence occurs after only a few tens of simulations (Sarma and Chen, 2008a, 2008b). Because of this advantage, recently, using gradient-based methods to find optimum well locations become attractive (Handles et al., 2007;

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Nomenclature

a_o	objective function coefficients for oil
a_g	objective function coefficients for gas
a_w	objective function coefficients for water
C_i	weighting coefficient
d_i	discount factor
$f_i(t)$	produced fluid rate
IE	injector efficiency
J	objective function
$N_{(t)}$	simulation time in fractional years
q_{li}	production rate of each corresponding producers for that injector
Q_{inj}	total water injected by the injector
Q_{oi}	total oil production for well i
Q_{gi}	total gas production for well i
Q_{wi}	total water production for well i
r_i	discount rate
T	ratio of the total days in simulation divided by 365
X_i	uncertainty parameters
Y	the recovery factor
λ	control parameter
Φ	Lagrange multiplier
V	constraint function with optimization

Wang et al., 2007; Sarma and Chen, 2008a, 2008b; Castineira et al., 2009). However, gradient-based algorithms are local optimum methods that may provide suboptimal results. Furthermore, well positions are usually treated as a discrete variable in reservoir simulation, which makes implementing gradient-based algorithms difficult. In reported studies, 2D reservoir models were used or a simple injector–producer pair was considered instead. Regardless, the application of gradient-based algorithms in a large-scale model requires further investigation.

The ideal way to operate the injectors and producers to maximize project value is another key point in waterflooding optimization in near offshore oil fields. Asheim (1998) carried out the earliest study; he maximized water sweep efficiency by controlling well production and injection rates in a 2D reservoir model. Later, Sudaryanto and Yortsos (2001) studied optimization rates to maximize the displacement efficiency at the injected fluid arrival time with a “bang bang” optimal policy. Afterwards, Brouwer and Jansen (2002) developed dynamic water flooding optimization algorithms for the valve settings in smart wells where adjoint models and gradient techniques were applied. Since then, the adjoint gradient-based technique has been explored and implemented extensively by many researchers such as Kraaijevanger et al. (2007) and Sarma and Chen (2008a, 2008b) in order to maximize the net present value (NPV) or the displacement efficiency. Their study proved that the adjoint gradient method could work efficiently, making it applicable in large reservoir simulation models.

In this paper, we use a systematic approach to optimize waterflooding design, including well placement and operation rates. The well-placement was optimized through an efficient, two-stage ranking-based method. In the first stage, it was assumed that every column of cell in the reservoir simulation model contained a pseudo-producer. Moreover, by applying the three well screening criteria, the least effective wells were eliminated based on their simulation performances. In the second stage, based on the streamline method, the injector placement was optimized to improve waterflooding sweep efficiency. Furthermore, the dynamic injection allocation and volumetric sweep efficiency of waterflooding patterns were described, while the relationship between injector and producer was qualified through streamline simulation. By using this ranking-based well placement optimization approach, optimum well placement is achieved using full field simulation runs. Two examples demonstrated the efficiency and applicability of this approach. Moreover, adjoint-based optimization algorithm was employed to optimize the water injection rate for each injector as well as the liquid production rate for each producer. This algorithm has been incorporated into the ECLIPSE reservoir simulation models, which provides a powerful and convenient tool for operation rate optimization.

This systematic integrated approach to well-placement optimization and waterflooding rate control has been applied to manage NP1-29 Block, a near offshore faulted reservoir in China. After optimization, 10-year cumulative oil production can be improved 16% and profit will increase above 20% over the conventional waterflooding design.

2. Method of well placement optimization

2.1. Producer placement optimization

Many reservoir characteristics such as layer thickness, oil saturation distributions, and permeability affect oil production performance. The aim of producer placement optimization is to identify the best locations for a given number of wells in order to maximize oil production potential. The optimization process is initialized by assuming that every column of cell in the reservoir simulation model contains a well except the exclusion zone where original producers or injectors exist. Then, the wells that have low oil-production potential are screened out based on the following three criteria (Schlumberger, 2008):

Step 1: good producers should be located in positions with sufficient oil reserves. In Step 1, all pseudo-wells were screened based on static constraints of reservoir properties—oil saturation, gas saturation, and layer thickness. By predefining threshold values of minimal saturation or layer thickness, the wells whose parameters were below these specified threshold values were eliminated, while the qualified grid blocks for new producers remained.

Step 2: a good producer should be located at a position with great oil mobility. Applying dynamic constraints further reduced the number of wells from Step 1. Dynamic constraints generally include production index, gas oil ratio, water cut, horizontal permeability or their combinations. Unlike static constraints read directly from the reservoir simulation model, a numerical simulation run was required to obtain the minimal and maximum bounds for these dynamic constraints. By setting bound values, the wells whose dynamic parameters were outside the specified ranges were disabled.

Step 3: finally, optimizing producer placement achieves maximum economic benefit. In this step, the following objective function J was evaluated as screening criteria to select the well placement through full simulation runs:

$$J = \sum_i (a_o \Delta Q_{oi} + a_g \Delta Q_{gi} + a_w \Delta Q_{wi})/(1+r_i)^T \qquad (1)$$

where, a_o, a_g and a_w are the objective function coefficients for oil, gas and water, r_i is the discount rate and T is the total simulation time in years.

The constant bottom-hole pressure was used as the operation constraint to conduct the reservoir simulation with all candidate