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A workflow for risk analysis and optimization of steam flooding scenario using static and dynamic proxy models

Hamed Panjalizadeh *, Nasser Alizadeh, Hadi Mashhadi

Amirkabir University of Technology, Tehran, Iran

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ABSTRACT

Heavy oil reservoirs are full of uncertainties because of the difficulties in fluid and core sampling as well as well testing operations. Therefore, making any decision on development plan of heavy oil reservoirs under strong uncertain conditions needs risk analysis.

Different thermal processes like steam injection have been used for the recovery of heavy oil. Because of high steam generation costs, it is necessary to optimize the process. But both risk analysis and optimization are very time consuming and expensive tasks as they both need too many simulation runs. Creating a proxy model, which replaces the simulator and emulates simulator outputs very fast, seems to be a good solution to this problem.

Different static proxy models have been used to-date, which can optimize the process only at one certain time of simulation and they are not valid for other times. In this study for the first time dynamic or time dependent proxy models are used for uncertainty analysis and optimization. The term dynamic or time-dependent proxy model is a response surface of desired objective parameters, which is valid for the whole time interval of the process.

This study demonstrates the application of artificial intelligence for optimization of steam flooding using dynamic proxy models. A new time-dependent artificial neural network is introduced as a dynamic response surface. By coupling this response surface with genetic algorithm, optimum injection conditions such as steam injection rate, steam quality, and also optimum injection time are obtained in a no-dip layered heavy oil reservoir. The proposed workflow is a rapid and cost-effective tool for risk analysis and optimization of steam flooding in heavy oil reservoirs.

1. Introduction

Nowadays, many oil companies use thermal processes like steam flooding and cyclic steam stimulation for the recovery of moderately viscous heavy oil from sand stone reservoirs (Das, 2007). In steam flooding process, steam is injected into the reservoir. Injecting steam with sufficient quality and rate is required for the process to be effective. However, the cost of steam generation is very high (Hong, 1994). Because of high steam generation cost, it is necessary to optimize this process before developing the heavy oil reservoir. Different steam injection conditions have been recommended by various researchers. (Hong, 1994; Li et al., 2005). For example, Hong concluded that optimum steam quality and injection rate in a pattern flood for a no-dip reservoir appear to be the highest values that can be obtained for the given heavy oil reservoir (Hong, 1994). In this study, steam quality, steam injection rate, and optimum time are optimized simultaneously.

Investigation of oil reservoirs, associating with various uncertain parameters under different EOR methods is a major issue in reservoir engineering. In heavy oil reservoirs, there are difficulties in fluid and core sampling as well as well testing operations. As a result, more uncertainties exist especially during their early development stages. In such cases, where the decisions about the entire field development process have to be taken under strong conditions of uncertainty, a probabilistic analysis seems to be a better way to proceed rather than a deterministic one (Prada et al., 2005).

In a risk methodology, geological uncertainties can be combined in Monte Carlo technique to obtain the range of uncertainty of some objective functions (Risso et al., 2008). Monte Carlo simulations require hundreds or thousands of simulation runs to provide meaningful results. Therefore, performing this method for the uncertainty analysis of reservoir simulation studies is impractical. (Mohaghegh, 2006). Stochastic optimization algorithms such as genetic algorithm have been used extensively to determine optimum conditions in different reservoir development problems. Using these algorithms

* Corresponding author.
E-mail addresses: panjalizadeh@aut.ac.ir (H. Panjalizadeh), ntabrizi@slb.com (N. Alizadeh), h.mashhadi@aut.ac.ir (H. Mashhadi).

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Nomenclature

3-Level	three level full factorial design
ANN	artificial neural network
BB	Box–Behnken design
BHP	maximum bottom hole injection pressure, psia
CCC	circumscribed central composite design
CCF	face-centered central composite design
CCI	inscribed central composite design
CDF	cumulative distribution function
CDNO	cumulative discounted net oil, STB
CWE	cold water equivalent
FOPT	field oil production total, STB
FOSRC	field oil steam ratio cumulative
$F_{s/f}$	steam/fuel ratio
GA	genetic algorithm
HEATTX	heat transmissibility multiplier in *x* direction
HEATTY	heat transmissibility multiplier in *y* direction
HEATTZ	heat transmissibility multiplier in z direction
MULTPV	pore volume multiplier
MULTRV	rock volume multiplier
MULTX	transmissibility multiplier in *x* direction
MULTY	transmissibility multiplier in *y* direction
MULTZ	transmissibility multiplier in *z* direction
$N_{p,ns}$	cumulative net sales produced oil, STB
P	probability
PR	polynomial regression
Q_{inj}	steam injection rate, STB/D, cold water equivalent
RE	relative prediction error
RSM	response surface methodology
RTC	rock thermal conductivity, Btu/(ft D °F)
SQ	steam quality
ST	steam temperature, °F
SWCR	critical water saturation
T-D	time-dependent
y	actual response
y'	transformed response
y^p	predicted response by proxy model
y^s	simulated response
λ	applied power transformation
Δt	time period for constant Qinj, days

requires a lot of simulation runs. Thus, both optimization and risk analysis are time-consuming and expensive procedures. Alternatively, developing a proxy or response surface such as an artificial neural network (ANN) or a polynomial regression (PR) model, which gives outputs close to the simulation results, seems to be an appropriate technique. Proxy models are extensively used in reservoir simulation studies. Polynomial regression models (PR), multivariate kriging models (KG), thin-plate splines models (TPS), or artificial neural networks (ANNs) are examples of proxy models used in these studies (Zubarev, 2009).

Experimental design can be used to generate a reliable response surface which covers the whole range of design space (NIST/SEMATECH e-Handbook of Statistical Methods, 2012). The first appearance of experimental design in the petroleum industry was in the early 1990s (Damsleth and Hage, 1991). In addition, ANN has already been used for forecasting (Huang et al., 2003), optimization (Queipo et al., 2002), and experimental design also has been applied in reservoir studies (Prada et al., 2005). A combination of experimental design and proxy models including ANN and PR models have been applied in dealing with uncertain systems (Jalali and Mohaghegh, 2009; Murtha et al., 2009).

Genetic algorithm has become very popular in reservoir optimization studies in the last two decades. The focus of these studies was mostly on well placement problems (Guyaguler and Gumrah, 1999). In addition, Patel et al. (2005) used genetic algorithm for optimization of a cyclic-steam injection project.

Direct optimization with stochastic optimization algorithms requires a lot of function evaluations and each function evaluation requires performing a simulation run. Then the objective function values can be calculated by using the resulting production data obtained from the simulation run. The simulation CPU requirements for large reservoir models are very high. Many studies were conducted to reduce this computational expense. Various methodologies were recommended by researchers. Onwunalu et al. (2008) applied statistical proxies to speed up field development optimization using genetic algorithm. Bittencourt and Horne (1997) and Yeten et al. (2002) developed a hybrid algorithm based on genetic algorithm, Polytope and Tabu search to obtain the best plan for the oil field development. Stoisits et al. (1999) used a neural network proxy to represent the components of the production system, and then used a simple GA to optimize production.

Different static proxy models have been used to-date, which can optimize the process only at one certain time of simulation and they are not valid for other times. In this study for the first time dynamic or time dependent proxy models are used for uncertainty analysis and optimization. The term dynamic or time-dependent proxy model is a response surface of desired objective parameters, which is valid for the whole time interval of the process. Although researchers have used proxy modeling optimization techniques, there is no evidence of time-dependent proxy modeling optimization in the literature.

This study demonstrates the application of artificial intelligence for optimization of steam flooding using dynamic proxy models. A new time-dependent artificial neural network is introduced as a dynamic response surface. By coupling this response surface with genetic algorithm, optimum injection conditions such as steam injection rate, steam quality, and also optimum injection time are obtained in a no-dip layered heavy oil reservoir. The proposed workflow is a rapid and cost-effective tool for risk analysis and optimization of steam flooding in heavy oil reservoirs.

2. Steam flooding model description

In this study, a steam displacement model of distillable heavy oil used by Aziz et al. (1985), which is a standard tested model and a pattern model as well, is used with some adjustments. It is an inverted nine-spot pattern by considering one-eighth of the full pattern. The model area is about 0.38 acres. Further information about this SPE model is available in the reference (Aziz et al., 1985). The introduced workflow has been successfully tested in real cases, but unfortunately the authors are unable to publish the results due to the confidentially of the data.

3. Methodologies

The steps of the workflow introduced in this study are as follows: (1) Definition of objectives and selection of possible uncertain parameters; (2) performing a screening and sensitivity analysis to find out the most influential uncertain parameters; (3) dataset sampling using response surface designs for constructing proxy