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Development of an adaptive surrogate model for production optimization

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ABSTRACT

Recently production optimization has gained increasing interest in the petroleum industry. The most computationally expensive part of the production optimization process is the evaluation of the objective function performed by a numerical reservoir simulator. Employing surrogate models (a.k.a. proxy models) as a substitute for the reservoir simulator is proposed for alleviating this high computational cost.

In this study, a novel approach for constructing adaptive surrogate models with application in production optimization problem is proposed. A dynamic Artificial Neural Networks (ANNs) is employed as the approximation function while the training is performed using an adaptive sampling algorithm. Multi-ANNs are initially trained using a small data set generated by a space filling sequential design. Then, the state-of-the-art adaptive sampling algorithm recursively adds training points to enhance prediction accuracy of the surrogate model using minimum number of expensive objective function evaluations. Jackknifing and Cross Validation (CV) methods are used during the recursive training and network assessment stages. The developed methodology is employed to optimize production on the bench marking PUNQ-S3 reservoir model. The Genetic Algorithm (GA) is used as the optimization algorithm in this study. Computational results confirm that the developed adaptive surrogate model outperforms the conventional one-shot approach achieving greater prediction accuracy while substantially reduces the computational cost. Performance of the production optimization process is investigated when the objective function evaluations are performed using the actual reservoir model and/or the surrogate model. The results show that the proposed surrogate modeling approach by providing a fast approximation of the actual reservoir simulation model with a good accuracy enhances the whole optimization process.

1. Introduction

Recent advances in computer science have greatly affected scientific fields. Nowadays, detailed numerical simulation with higher accuracy has been frequently used as a powerful tool for engineering design and optimization. Numerical simulation of petroleum reservoirs, as the most accurate available tool to predict the fluid flow behavior in the reservoir, is frequently used in all levels of field development in the oil and gas industry. In order to perform an optimization task, hundreds or thousands reservoir simulation runs are required. A single run of the simulated reservoir model, which is made of thousands or even millions of grid blocks, takes several hours. Moreover, the large number of control parameters exacerbates this reservoir simulation-based optimum design problem. Surrogate model (also known as Meta model or proxy model) is an approximation function that mimics the original system's behavior, but can be evaluated much faster (Crombecq et al., 2011). Developed surrogate model partly or completely substitute the full reservoir model to reduce the computation time associated with running full reservoir model as the objective function. In the petroleum engineering literature, various works have been done in the field of surrogate modeling (Badru and Kabir, 2003; Haghighat Sefat et al., 2012; Mohaghegh, 2011; Ozdogan et al., 2005). Centilmen et al. (1999) trained an ANN to be used in well placement optimization problem. They selected several key wells scenarios and evaluated them using a numerical reservoir simulator. The simulation results were used to train an ANN. Finally, the ANN was used as a fast predictive tool for optimizing locations of the new wells in the reservoir. Guyaguler et al. (2000) proposed a hybrid optimization technique using GA employing surrogate model developed by ordinary Kriging algorithm as the approximation function. They used this approach to optimize the location of new injection wells and their

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Nomenclature

Acronyms

ANN	Artificial Neural Network
ASP	Alkaline-Surfactant-Polymer
BHP	Bottom Hole Pressure
CV	Cross-Validation
DACE	Design and Analysis of Computer Experiment
DOE	Design Of Experiment
GA	Genetic Algorithm
NPV	Net Present Value
RBF	Radial Basis Function
RE	Relative Error
RM	Reservoir Model
ROM	Reduced Order Models
SAGD	Steam Assisted Gravity Drainage
SM	Surrogate Model

Symbols

b	discount rate, percent per years
c	nonlinear constraint
C	number of candidate points
f	true function
$\hat{f}$	approximation function
H	number of hidden neurons
J	objective function
k	number of input variables
L	number of inputs of ANN
M	number of outputs of ANN
N	number of fold in N-fold cross-validation
np	number of wells
nt	total number of control steps
p^t	elapsed time, year
Q_i^t	total field water injection rate of t^{th} control step, STB/day
Q_o^t	total field oil production rate of t^{th} control step, STB/day
Q_w^t	total field water production rate of t^{th} control step, STB/day
R	design space of variables
r_i	cost of water injection, USD/STB
r_o	oil price, USD/STB
r_w	cost of water removal, USD/STB
$s(t)$	transfer function
S	training data set
$\tilde{s}$	jackknife variance
t	control step
$\mathbf{u}$	vector of control variables
X	input data
y	simulation output
Y	Output data
$\hat{y}$	surrogate model prediction
$\tilde{y}$	Jackknife estimate
$\bar{\tilde{y}}$	Average of jackknife estimate
$\mathbf{Z}$	input matrix of ANN

Greek symbols

$\theta(\omega, \eta, \mu, \zeta)$	weights of ANN
Δt	difference between two control steps, day

corresponding rate in a water flooding project in the Gulf of Mexico Pompano field. Queipo et al. (2002) constructed a surrogate model employing ANN as the approximation function while using DACE (Design and Analysis of Computer Experiment) methodology for the experimental design. The developed surrogate model is used to optimize the operational parameters of a Steam Assisted Gravity Drainage (SAGD) process. Zerpa et al. (2005) employed multiple surrogate models coupled with a global optimization algorithm to estimate optimal design variables of Alkaline-Surfactant-Polymer (ASP) flooding process. Castellini et al. (2010) used thin-plate spline regression techniques to construct the surrogate model. They employed an iterative sampling strategy to capture the non-linear behavior of the underlying system and efficiently refine the surrogate model.

Most of these studies have used one-shot approach to develop the surrogate model. In one-shot approach the surrogate model is constructed during one stage and will be used for all future optimization without further updates. However, one-shot approach has a main problem as generally the number of training points needed to achieve an acceptable accuracy is not known in advance while we are interested to train the surrogate model with as few as possible number of points. Adaptive sampling approach by sequentially selecting the training points addresses this problem.

In this study, an adaptive surrogate model is developed for the application in production optimization problem. The large number of control variables and response parameters is addressed by

1. Using a dynamic ANN as the approximation function.
2. A modified problem definition while the network receives consecutive well control parameters and sequentially predicts the points of the cumulative production curves of interest.
3. Developing individual surrogate model for predicting each output parameter (e.g. one surrogate model for predicting oil and another one for predicting water).

The outline of this manuscript is as follows. In Section 2, different stages of the surrogate modeling process are explained. Section 3 presents details of the developed framework. Section 4 shows the numerical results on the PUNQ-S3 case study. Optimization is performed using GA while the developed surrogate model and/or the actual reservoir model evaluates the objective function. Section 5 presents the general conclusions.

2. Constructing the surrogate model

Surrogate models, according to their approximation strategy, can be divided into two main categories: (1) model driven or physics based approach (Cardoso and Durlofsky, 2010; He et al., 2011; Rousset et al., 2014; Wilson and Durlofsky, 2013) and (2) data driven or black box approach (Jones et al., 1998; Keane and Nair, 2005; Kleijnen, 2007). Model driven approaches, known as Reduced Order Models (ROM), approximate the original equations with lower order equations and finally reduce the computational cost. To apply these approaches access to the reservoir simulator source codes is required which is generally impossible when using a commercial reservoir simulator. In contrast, data driven approaches by considering the reservoir simulator as a black-box, generate the surrogate model using only input data and output responses. The data driven approach is the focus of this study.