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Application of multi-criterion robust optimization in water-flooding of oil reservoir

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ABSTRACT

Most of the reported robust and non-robust optimization works are formulated based on a single-objective optimization, commonly in terms of net present value. However, variation of economical parameters such as oil price and costs forces such high computational optimization works to regenerate their optimum water injection policies. Furthermore, dynamic optimization strategies of water-flooding often lack robustness to geological uncertainties. This paper presents a multi-objective while robust optimization methodology by incorporating three dedicated objective functions. The goal is to determine optimized and robust water injection policies for all injection wells. It focuses on reducing the sensitivity to the uncertainty in the model and objective function parameters when no measurement information is assumed to be available. This work also, utilizes a derivative-free Evolutionary Multi-objective Optimization (EMO) procedure in the form of a Non-dominated Sorting Genetic Algorithm (NSGA) which attempts to find a robust Pareto-optimal solution without a priori knowledge of the reservoir dynamic models. Some modifications have been introduced to the original NSGA-II code to handle the constraints of the optimization problem. The comparative test studies clearly demonstrate superiority of the proposed methodology to give optimal robust solutions under geological uncertainties with much less standard deviations and variances. Furthermore, the optimization results demonstrate less sensitivity to the imposed time-varying economical parameters such as operation costs and oil price, revealing non-dependency of the introduced multi-objective functions.

1. Introduction

1.1. Water-flooding process

Fundamentally, water-flood involves pumping water through a well (injector) into the reservoir. The water is forced through the pore spaces and sweeps the oil towards the producing wells (producers). The percentage of water in the produced fluids steadily increases until the cost of removing and disposing of water exceeds the income from oil production. After this point, it becomes uneconomical to continue the operation and the water-flooding is stopped. On the average, about one-third of the original oil in place (OOIP) is recovered, leaving two-thirds behind after secondary recovery. Product optimization of water-flooding has shown a significant potential to increase ultimate recovery (Brouwer and Jansen, 2004; Jansen et al., 2005; Sarma et al., 2005; Wang et al., 2007; Sarma et al., 2008). A single objective function, known as production or net present value, has been considered as the objective function in all the previous investigations reported in the literature.

1.2. Uncertainties and robust optimization

Dealing with uncertainty is an important topic encountered in many fields related to modeling and control. Reducing the uncertainty itself, using measurements and reducing the sensitivity to the uncertainty are two different strategies which are not basically conflicting with each other (Van Essen et al., 2009).

Beyer and Sendhoff (2007) in their survey classified modeling of the uncertainties to deterministically, probabilistically, or possibilistically. The deterministic type defines parameter domains in which the uncertainties can vary; the probabilistic type defines probability measures describing the likelihood by which a certain event occurs. The possibilistic type defines fuzzy measures describing the possibility or membership grade by which a certain event can be plausible or believable. However, a publically-accepted remedy for various technologies that suffer from vast uncertainties of any above-mentioned

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Nomenclature

b	discount rate (%/year)
E	expected value operator
f	objective functions
g	inequality constraints
h	equality constraints
J	objective function
$\bar{J}$	modified objective function
k	time-step counter
K	total number of time steps
N	number of wells
N_T	total number of realizations
N_R	number of small set of realizations
q	flow rate (m^3/day)
r	risk aversion factor – price (\$/m^3)
t	time (day)
t_k	time at time step k (day)
Δt_k	time interval of time step k (day)
x	manipulated variable
θ_d	finite number of realizations
θ_R	representative realizations set
Θ	unknown uncertainty space
τ_I	reference time (365 days)
Σ_{θ_d}	standard deviation
Φ	volumetric ratio

Subscripts

c, o, p	cumulative oil production
c, w, i	cumulative water injection
$i, well$	injection well
l, p	liquid production rate
o	oil
$o, Total$	total oil in place
$p, well$	production well
RO	robust optimization
$w\ i$	injected water
$w\ p$	produced waters
w, p	water production rate

classes – yet alone with limited measurements – is the use of a so-called *robust* optimization.

Since the uncertainties in upstream petroleum industries are high, conventional optimization strategies are not amenable to carry over the optimization task deliberately.

Van Essen et al. (2009) presented an approach to reduce the impact of geological uncertainties in the field development phase known as a robust optimization (RO). Their proposed RO scheme uses a set of realizations that reflect the range of possible geological structures honoring the statistics of the geological uncertainties. The associated objective function was NPV in terms of a *single* objective with pre-defined costs and oil price. They used a classical gradient-based optimization method where the gradients were obtained with an adjoint formulation.

The approach of Alhuthali et al. (2010) relies on equalizing arrival time of the waterfront at all producers using multiple geologic realizations. They account for geologic uncertainty using two optimization schemes: a stochastic form which relies on a combination of expected value and standard deviation combined with a risk attitude coefficient. This approach is some sort of scalarization of a bi-objective optimization problem which can be solved by single objective optimizer engines. Their approach was the analytical computation of the gradient and Hessian of the objective function.

Almeida et al. (2010) presented an evolutionary algorithm-based decision support system able to optimize intelligent well control, in intelligent oil fields, under technical and geological uncertainties. A genetic algorithm was used for obtaining a pro-active control strategy and determining an operation that maximized the single objective net present value (NPV).

The objective of Chen and Hoo (2012) is to optimize oil production by managing the amount of water added to a reservoir. This management is accomplished by employing an optimal model-based control framework that includes uncertain parameter updating and a particular low-order model identified from a first-principles model.

Nevertheless, to the best of our knowledge, none of the reported works consider uncertainty in the objective function parameters. As it is clear, time varying parameters in the objective function, especially oil price could force a huge persuasion to recalculate the time-consuming optimization work. In this paper by introducing three specific objective functions, a new approach will be proposed to calculate the *robust Pareto-front* in the defined multi-objective optimization problems.

Uncertainty of any geological model due to insufficient data is an inherent characteristic. To cope with the geological uncertainty in the reservoir, a number of realizations that are equally probable and reflect the range of possible geological structures, are generated and robust optimization can be performed based on these realizations using the specific objective functions.

Reducing the uncertainty using measurement is known as *history matching*. In the present study reducing the sensitivity to the uncertainty was the main goal and optimization was performed in the absence of measurement. Reducing the sensitivity for two types of uncertainty has been covered through this work: *uncertainty in the reservoir model* and *uncertainty in the parameters of the objective functions*.

This paper addresses the secondary recovery phase of a petroleum reservoir using water-flooding based on a multi-objective robust optimization scheme.

2. Optimization algorithm

Most efficient methods used in solving optimization problems rely on explicit knowledge of the underlying simulator equations to compute the gradient of the objective function. As a result of large and complicated nature of reservoir models with large number of unknowns and non-linear constraints, the software for gradient calculations will be very tedious and time-consuming to create for practical optimization problems. Yet, another major drawback of the gradient-based methods using adjoint equations is that it requires explicit knowledge of the simulation model equations describing the dynamic behavior of the system. By using derivative-free methods like Genetic Algorithm (GA), no knowledge of the simulator equations is required and the simulator can be run as a black box. GA does not require any derivative information and is less likely to be trapped in local minima. It also has the ability to optimize discrete (and thus non-differentiable) variables such as the control settings. GA has therefore been utilized as an influential tool for solution of various problems in reservoir engineering.

Unlike the gradient-based methods, GA typically converges slowly and becomes inefficient when a large number of variables