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Dynamic Self-Optimizing Control for Oil Reservoir Waterflooding

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Abstract: Waterflooding is a common oil recovery method where water is injected into the reservoir for increased productivity. Optimal operational strategy of waterflooding processes has to consider proceeds realized from produced oil and cost of productions including both injected and produced water. This is a dynamic optimization problem. The problem could be solved through numerical algorithms based on traditional optimal control theory which can provide only open-loop control solutions and rely on an accurate process model. However, reservoir properties are extremely uncertain, and hence open-loop solutions based on a nominal model are not suitable for applications with real reservoirs. Introduction of feedback into the optimization structure to counteract the effect of uncertainties has been proposed recently. In this work, a novel feedback optimization method for optimal waterflooding operation is presented. In the approach, appropriate controlled variables as combinations of measurement histories and manipulated variables are first derived through regression based on simulation data obtained from a nominal model. Then a feedback control law was represented as a linear function of measurement histories from the controlled variables obtained. Through a case study, it was shown that the feedback control solution proposed in this work was able to achieve a near-optimal operational profit with only 0.45% worse than that achieved through the true optimal control (with system's properties assumed to be known a priori), but 95.05% better than that obtained with the open-loop solution under uncertainties.

Keywords: Reservoir waterflooding, Optimal control, Self-optimizing control, Open-loop solution, Controlled variable.

1. INTRODUCTION

The prudent search for efficient recovery methods of oil from ageing reservoirs has sprung studies on optimization techniques for reservoir waterflooding. Waterflooding is the most common type of secondary recovery methods (Adeniyi et al., 2008) which involves injection of water into the reservoir through an injection well with the aim to properly sweep the oil in place towards a production well and/or maintain the reservoir pressure (Grema and Cao, 2013).

A typical waterflooding optimization problem seeks to determine optimum injection and production settings in order to maximize a performance index such as net present value (NPV) or total oil recovery. Several works were reported to employ the traditional optimal control which provides an open-loop solution based on an off-line nominal model (Asadollahi and Naevdal, 2009; Brouwer and Jansen, 2004). Unfortunately, reservoir properties including its geometry and boundaries are uncertain (Jansen et al., 2008). There are some production behaviours that can rarely be captured well through simulation model such as well coning (Dilib and Jackson, 2013a). Therefore, for a real oil reservoir, open-loop optimal solution determined off-line from a model may be suboptimal or entirely non-optimal.

Several methods have been proposed in the literature to deal with such uncertainties. For example, in robust optimization (RO), inputs are implemented in an open-loop fashion which have to follow a predetermined profile such that system constraints are satisfied in the presence of any uncertainty or disturbance (Yeten et al., 2003; Ye et al., 2013; Gabrel et al., 2014). Because RO approaches are designed to account for all possible uncertainties, their performance is mostly conservative which hardly leads to an optimal solution. Works that reported to use such technique in the field of waterflooding include that of van Essen and others (van Essen et al., 2009). It involves use of a set of reservoir realizations with the assumption that it captures all reservoir characteristics and production behaviours, a condition which is very difficult to be met in reality. Another method developed to counteract the effects of uncertainties is parametric optimization technique (Fotiou et al., 2006). Never the less, the method is too complicated to be applicable to waterflooding processes. Stochastic optimization methods were also developed to counter the effects of systems uncertainties (Tu and Lu, 2003; Pastorino, 2007; Wu, 2012). These methods involve random search within a parameter space in which potential solutions are evaluated. (Collet and Rennard, 2007). Slow convergence and high computational power requirement is a major drawback to these methods. A practical approach, repeated learning control was developed for batch processes (Ganping and Jun, 2011; Ahn et al., 2014), unfortunately it is not applicable to processes that are not repeatable, typical of petroleum production from reservoirs.

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The current practice in industries is a procedure that is commonly referred to as history matching which involves periodic updating of available reservoir models using historical data and subsequent determination of operational strategies based on the updated models. However, solutions based on history-matched models may be suboptimal or non-optimal at all because of inability of updated models to predict reality correctly.

Based on the fact that feedback is an efficient tool to deal with uncertainties, proposals have been made recently of including a direct feedback control for optimal waterflooding operations (Jansen et al., 2008; Dilib and Jackson, 2013a; Brouwer et al., 2001; Foss, B. and Jensen,J. P., 2011). But a fundamental task that has not been investigated is formulation of a simple controlled variable (CV) that should make the optimality of waterflooding process insensitive to various geological uncertainties. Recently, we have developed a robust CV based on the principle of self-optimizing control (SOC) and tested it on a system with one degree of freedom (DOF) (Grema and Cao, 2014). In that work, an optimal feedback control law was represented as a linear function of production measurements with coefficients to be determined through least square regression to approximate the gradient of the cost function against manipulated variables based on simulated data obtained from a nominal model. The whole idea is to maintain the selected CV at zero through feedback control so that the operation is automatically optimal or near optimal with an acceptable loss.

This work extended the methodology presented by (Grema and Cao, 2014) to solve multivariable waterflooding optimization problem. Results obtained were compared with the open-loop optimal control approach for cases with different uncertainties. Furthermore, true optimal control solutions where the system model was assumed to be perfect with all properties known a priori are also derived as a benchmark for the above comparison.

2. APPROACH

2.1 Dynamic Optimization for Reservoir Waterflooding using SOC

A reservoir model in a discretized form is given as

$$\boldsymbol{g}(\boldsymbol{u}^k, \boldsymbol{x}^{k+1}, \boldsymbol{x}^k) = \mathbf{0} \tag{1}$$

where $\boldsymbol{x}^k$ and $\boldsymbol{u}^k$ are the state and input vectors respectively at time-step, k. For such kind of system, an objective function, J to be optimized can be represented as

$$J = \sum_{k=1}^{N} J^k(\boldsymbol{u}^k, \boldsymbol{y}^k) \tag{2}$$

where J consists of contributions at each time step denoted by J^k, $\boldsymbol{y}^k$ is a vector of measurements at time step k, and N is the total number of time steps. From (1), it can be inferred that any change in $\boldsymbol{u}^k$ at time k will affect the states $\boldsymbol{x}^{k+1}$, which will in turn influence the outputs, $\boldsymbol{y}^{k+1}$ through some measurement functions

$$\boldsymbol{h}(\boldsymbol{x}^k, \boldsymbol{y}^k) = \mathbf{0} \tag{3}$$

A feedback control law is sought to maintain the gradient of the objective function with respect to control input to be zero or near zero at each time step such that the overall trajectory is optimal or near optimal, i.e. the objective function is minimum or near minimum in the presence of uncertainties. If any two or more control trajectories are perturbed, then the deviation of the cost function J, can be approximated by finite differences between two closely related trajectories, $\boldsymbol{u}_i^1, \boldsymbol{u}_i^2, \ldots, \boldsymbol{u}_i^N$ and $\boldsymbol{u}_{i+1}^1, \boldsymbol{u}_{i+1}^2, \ldots, \boldsymbol{u}_{i+1}^N$, if $\max\|\boldsymbol{u}_{i+1}^k - \boldsymbol{u}_i^k\| < \varepsilon$ with a sufficiently small ε. The deviation in the cost function can be written using Taylor's series expansion as

$$J_{i+1} - J_i = \sum_{j=1}^{n_u} \sum_{k=1}^{N} G_{i,j}^k (u_{i+1,j}^k - u_{i,j}^k) \tag{4}$$

where n_u is the total number of inputs and $G_{i,j}^k$ is the gradient of the objective function with respect to the input channel, j at time-step, k for the reference trajectory, i.

Generally, the analytical expression of the gradient function in (4) is difficult to obtain particularly in the presence of uncertainties. To derive an output feedback control law, $\boldsymbol{u}^k = \boldsymbol{F}(\boldsymbol{y}_i^k, \boldsymbol{y}_i^{k-1}, \ldots \boldsymbol{y}_i^{k-n})$, which is equivalent to $\boldsymbol{F}(\boldsymbol{y}_i^k, \boldsymbol{y}_i^{k-1}, \ldots \boldsymbol{y}_i^{k-n}) - \boldsymbol{u}^k = 0$, it is proposed to approximate these gradients by a number of measurement functions with a set of unknown parameters to be determined through regression based on simulated data. Therefore, the gradient in (4) can be replaced by a measurement function, C as

$$J_{i+1} - J_i = \sum_{j=1}^{n_u} \sum_{k=n+1}^{N} [C(\boldsymbol{\theta}_j, \boldsymbol{y}_i^k, \boldsymbol{y}_i^{k-1}, \ldots \boldsymbol{y}_i^{k-n}, u_{i,j}^k) \\ (u_{i+1,j}^k - u_{i,j}^k)] \tag{5}$$

where θ_j is a parameter vector to be determined through regression for channel j and the measurement vector includes current and past measurements with n being the number of histories, which was found to be 2 after some trial and error exercises in this study. C can be any polynomial function such that $\boldsymbol{u}^k$ can be easily obtainable, but a linear combination of measurements was adopted in this work.

For simulated data collection, the following steps are followed:

1. A control trajectory, i is found via optimal control computation given as
$$\boldsymbol{u}_i^1, \boldsymbol{u}_i^2, \ldots\ldots\ldots\ldots. \boldsymbol{u}_i^N,$$
2. The control trajectory above is used to solve the model equation in (1) where measurements and states sequences are obtained which are given respectively as:
$\boldsymbol{y}_i^0, \boldsymbol{y}_i^1, \boldsymbol{y}_i^2 \ldots. \boldsymbol{y}_i^N$ and $\boldsymbol{x}_i^0, \boldsymbol{x}_i^1, \boldsymbol{x}_i^2 \ldots\ldots \boldsymbol{x}_i^N$,
3. The control trajectory in step 1 is perturbed to $\boldsymbol{u}_{i+1}^1, \boldsymbol{u}_{i+1}^2, \ldots. \boldsymbol{u}_{i+1}^N$ and the model is solved where perturbed measurements $\boldsymbol{y}_{i+1}^0, \boldsymbol{y}_{i+1}^1, \boldsymbol{y}_{i+1}^2 \ldots\ldots \boldsymbol{y}_{i+1}^N$,