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Data-Driven Self-Optimizing Control for Petroleum Reservoir Waterflooding

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Abstract
As reservoir states change with time, changing injection and production settings will be required for optimal oil production during waterflooding process. The determination of these settings is actually a dynamic optimization problem which could be solved through optimal control methods that provide only open-loop solutions. However, due to huge uncertainties that characterize reservoir properties, these techniques were found to be sensitive to model/system mismatch. In this work two feedback optimization methods were developed and compared for reservoir waterflooding with the aim to counteract the effects of uncertainties. The first is based on principles of receding horizon control (RHC) while the second was developed from self-optimizing control (SOC) method. In the SOC method, appropriate controlled variables (CVs) as combinations of measurement histories and manipulated variables are first derived through regression based on simulation data obtained from a nominal model. Then the optimal feedback control law was represented as a linear function of measurement histories from the CVs obtained. Based on simulation studies, the RHC approach was found to be very sensitive to uncertainties when the nominal model differed significantly from the conceived real reservoir. The SOC methodology on the other hand, was shown to achieve an operational profit with only 2% worse than the true optimal control, but 30% better than the open-loop optimal control under the same uncertainties. The simplicity of the developed SOC approach coupled with its robustness to handle uncertainties proved its potentials to real industrial applications.
Keywords: Optimal control, receding horizon control, self-optimizing control, geological uncertainty, controlled variable

1.0 Introduction

Increase in world population has led to a corresponding increase in energy demand; it has been projected that oil and gas resources will continue to meet this needs for decades to come. Oil and gas are naturally occurring hydrocarbon which are found beneath the earth surface. The usual practice of recovery involves drilling of wells to strike the hydrocarbon accumulations which go to the surface by virtue of hydrostatic pressure. Oil recovery is classified into three phases on the basis of reservoir pressure. The pressure is usually very high for a new discovered reservoir which is sufficient to bring the oil to the surface in *primary recovery phase*. As production progresses the reservoir pressure is severely reduced. This pressure is supported by injecting fluids into the reservoir in *secondary recovery phase*. When water is used as the injecting fluids, the process is called *waterflooding* (Grema, 2014). Waterflooding is the commonest type of secondary recovery methods and perhaps, the cheapest. However, early water break-through and low sweep efficiency have been problems to waterflooding operation due to heterogeneity nature of reservoir. One of the solutions to these problems that is receiving great attention is the use of smart injection and production wells (Brouwer and Jansen, 2004; Grema *et al.*, 2016, 2015; Grema and Cao, 2016, 2013). Smart wells are nonconventional wells that are equipped downhole with inflow control valves (ICVs). They provide opportunity for control and optimization for the process.

Waterflooding optimization seeks to determine injection and production trajectories that will optimize an objective such as net present value or oil recovery. Several works were reported to have used the traditional optimal control theory which relies on an off-line nominal model to give open-loop solutions (Grema *et al*., 2016). However, reservoir systems can hardly be described correctly using models. Its properties such as geometry, size, porosity, permeability and etc. are highly uncertain.
A lot of methods have been proposed in the past to counteract the effect of model/system mismatches. These include robust optimization (RO) (Yeten and Durlofsky, 2003); parametric optimization (Fotiou *et al*., 2006); stochastic optimization (Pastorino, 2007); and repeated learning control (Gangping and Jun, 2011). These methods are either too conservative, complicated, slow in convergence or not applicable to reservoir production.
In this work, a novel data-driven self-optimizing control (SOC) approach was developed and its performance in counteracting effects of uncertainties is compared with those of open-loop control (OC) and receding horizon control (RHC).

2.0 Material and Methods

2.1 Reservoir Systems Dynamics

In reservoir waterflooding, the objective function to be maximized can be written in the following form for a total number of time steps N

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

The contribution to J in each time step is given by J^k, where $\boldsymbol{u}^k$, $\boldsymbol{y}^k$, and , $\boldsymbol{d}^k$are controls, measurements and disturbances respectively at time steps k. The reservoir models can be written in a discretized form as

$$\boldsymbol{g}(\boldsymbol{u}^k, \boldsymbol{x}^{k+1}, \boldsymbol{x}^k, \boldsymbol{\varphi}) = \boldsymbol{0} \qquad 2$$

where $\boldsymbol{x}^k$ is the reservoir states vector and $\boldsymbol{\varphi}$ vector of model parameters. A change in $\boldsymbol{u}^k$, at time k will not only affect J^k directly but will affect the states $\boldsymbol{x}^{k+1}$ according to Equation **Error! Reference source not found.**2). The states will in turn influence the outputs, $\mathbf{y}^{k+1}$, through the measurement equations as

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

2.2 Receding Horizon Control for Reservoir Production

Uncertainties in reservoir properties such as permeability, porosity and structure are dealt with using RHC. The study utilizes two different reservoir models; a prediction model for determination of optimal well settings and implementation model for implementation of the optimized well settings. The basic assumption was that, the implementation model served as the real reservoir who's some of its properties are uncertain. A benchmark solution (BM) case was also developed with assumption of a perfect reservoir model and properties known a priori. The steps are:

1. Initial states are chosen for the prediction model based on initial measurements from the real reservoir. This helps to minimize possible difference in real and predicted measurements.
2. Using the prediction model, optimal control inputs are determined for the starting step.
3. The optimal inputs $\boldsymbol{u_{opt}}$ found in Step 2 are applied to both the RHC and real reservoir models to make available two sets of measurements, predicted, $\boldsymbol{Y_p}$ and real, $\boldsymbol{Y}$ measurements respectively.
4. Output disturbance, $\boldsymbol{d}$ is computed as the difference between $\boldsymbol{Y}$ and $\boldsymbol{Y_p}$. An update on $\boldsymbol{Y_p}$ is made by adding the disturbance.
5. The control inputs for the second time step are obtained via optimization based on the updated measurements. These inputs are also applied to both models.
6. Steps 3 – 5 are repeatedly performed till the end of production time.

A simple diagram illustrating the above loop is shown in Fig. 1.

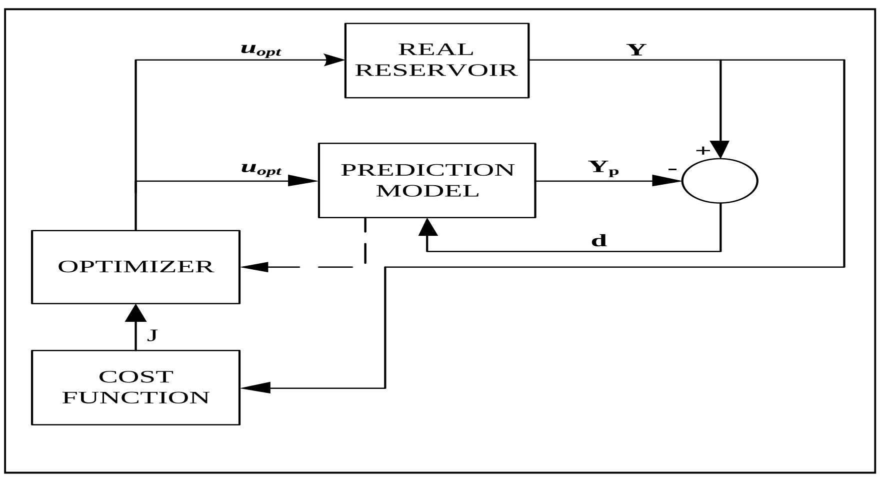

Fig. 1: Receding Horizon Control Loop

2.3 Self-Optimizing Control for Reservoir Production

To use the principles of SOC in optimizing reservoir waterflooding process, two main steps are undertaken which are offline determination of CV and online implementation. The offline procedures are as follow (Grema and Cao, 2016):

1. A control sequence is defined as
$$\boldsymbol{u}_i^1, \boldsymbol{u}_i^2, \dots \dots \dots \dots . \boldsymbol{u}_i^N,$$
the reservoir model Equation **Error! Reference source not found.**2) is solved to obtain a solution sequence
$$\boldsymbol{x}_i^0, \boldsymbol{x}_i^1, \boldsymbol{x}_i^2 \dots \dots . \boldsymbol{x}_i^N,$$
a measurement sequence
$$\boldsymbol{y}_i^0, \boldsymbol{y}_i^1, \boldsymbol{y}_i^2 \dots \dots . \boldsymbol{y}_i^N,$$
and a cost J_i
2. The control sequence is perturbed to
$$\boldsymbol{u}_{i+1}^1, \boldsymbol{u}_{i+1}^2, \dots . \boldsymbol{u}_{i+1}^N,$$
the reservoir model Equation 2 is then solved again to get perturbed solutions

$$\boldsymbol{x}_{i+1}^{0}, \boldsymbol{x}_{i+1}^{1}, \boldsymbol{x}_{i+1}^{2} \dots \dots . \boldsymbol{x}_{i+1}^{N},$$

measurements

$$\boldsymbol{y}_{i+1}^{0}, \boldsymbol{y}_{i+1}^{1}, \boldsymbol{y}_{i+1}^{2} \dots \dots . \boldsymbol{y}_{i+1}^{N},$$

and cost J_{i+1}.

3. The gradient of the objective function with respect to control is approximated using Taylor series expansion.

If $n_u$is the dimension of the control, $\boldsymbol{u}$**,** the gradient of the objective function with respect to $\boldsymbol{u}$ at each time step considering a reference trajectory, i with a neighbourhood $i+1$ is given by Taylor series expansion as

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

where $G_{i,j}^{k}$ is a gradient of the objective function with respect to an input channel, i at time-step, k and n number of past histories. The aim of dynamic SOC is at all time-steps to maintain the gradient at zero. Therefore, the gradient in Equation **Error! Reference source not found.**4) which is time-dependent can be replaced by a measurement function that can be used as a target CV whose value will remain constant at all time-steps irrespective of the magnitudes of the individual measurements, this is shown in Equation (5) as

$$J_{i+1} - J_i = \sum_{j=1}^{n_u} \sum_{k=n+1}^{N} C\left(\boldsymbol{\theta}_j, \boldsymbol{y}_i^{k}, \boldsymbol{y}_i^{k-1}, \dots \boldsymbol{y}_i^{k-n}, u_{i,j}^{k}\right)\left(u_{i+1,j}^{k} - u_{i,j}^{k}\right) \qquad 5$$

where $\boldsymbol{\theta}_j$ is a parameter vector to be determined through regression (Grema and Cao, 2016). Online CV implementation is shown in Figure 2.

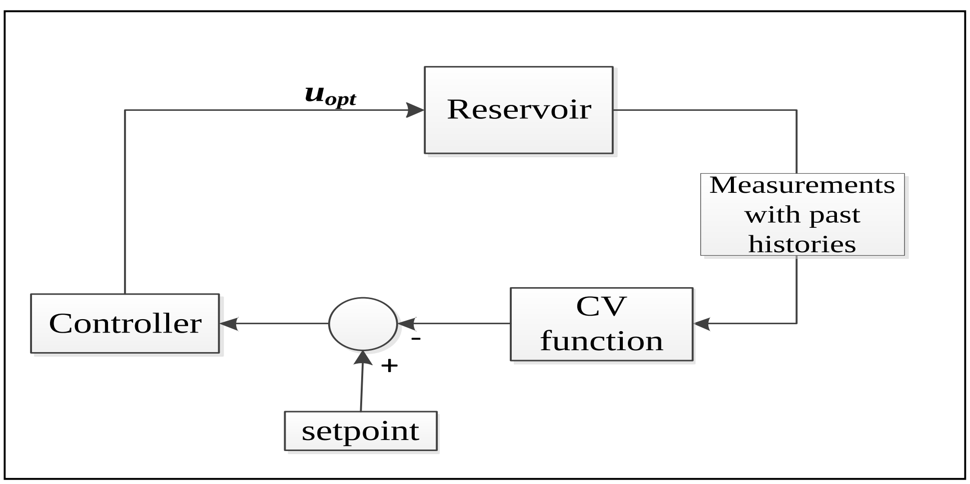

Fig. 2: Implementation of Feedback Control Law

2.4 Performance Evaluation

The performance of each approach was evaluated using two indices, loss given as

$$Loss = \frac{J_{BM} - J_{RHC/SOC/OC}}{J_{BM}} \times 100\% \qquad (6)$$

and gain as

$$Gain = \frac{J_{RHC/SOC} - J_{OC}}{J_{RHC/OC}} \times 100\% \quad (7)$$

where J_{BM} is NPV obtained by a bench mark method, $J_{RHC/SOC/OC}$ NPV obtained by either RHC, SOC or OC method.

2.5 Case Studies

Four different cases were considered. For the first case, uncertainty has not been introduced; nominal model was used. The reservoir adopted here as the nominal model which is a reservoir of size 20 m x 20 m x 5 m and homogenous in all fluid and rock properties. Specifically, the porosity and permeability are 0.3 and 100 mD respectively. As stated earlier, it is expected that RHC and SOC solutions for this case would not be as good as open-loop optimal control due to the absence of model/system mismatch. However, the case would serve as a basis of comparison with other uncertainty cases. In Case II, the nominal reservoir model differed from the real reservoir in permeability. All other properties of rocks, fluid, geometry and well configuration remain the same. The truth reservoir however, has five layers each with different permeability which is log-normally distributed with mean values of 200 mD, 500 mD, 350 mD, 700 mD, and 250 mD from top to bottom. In addition to uncertainty in permeability, rock porosity was also assumed to be uncertain in Case III. The setup is the same as in Case II but the porosity of the truth reservoir and the nominal model differs. Here, the nominal porosity remains at 0.3 while the real reservoir has a porosity of 0.45.

A lot of geological uncertainties were incorporated in Case IV which range from uncertainties in reservoir size, geometry and structure. The real reservoir was considered to be appreciably larger than the nominal reservoir whose size is 225 m x 22.5 m x 1 m. It was modelled with 30 x 3x 1 cells using a corner point gridding system. It also has a structural fault with width of 0.12 m. The fault can transmit fluids if the pressure drop across it is sufficient. Other rock and fluid properties are the same for both reservoirs (Grema and Cao, 2016).

3.0 Results and Discussions

A summary of the comparative study is given in Table 1. It can be seen from Table 1 that for the four cases, loses incurred by RHC approach are higher. In fact, an unacceptable loss of 15.21% resulted in Case IV as a result of implementing this feedback technique whereas the loss is only 2.09% for the same case by employing SOC approach. Based on these results, RHC can be said to be sensitive to model/system mismatch. The sensitivity of the formulated CV through SOC principle is however very minimal in comparison.

Table 1: Comparison between RHC and SOC Methods

	NPV ($)				Loss (%)	
Cases	**BM**	**SOC**	**RHC**	**OC**	**SOC**	**RHC**
I	182,775.00	182,297.70	182,274.70	182,775.00	-	-
II	159,723.50	159,428.90	159,320	159,096.40	0.19	0.25
III	239,271.50	228,116.4	222,286.10	220,918.20	4.66	7.10
IV	487,520.10	477,309.60	413,365.02	333,904.70	2.09	15.21

4.0 Conclusions

The feedback benefits of SOC in counteracting uncertainties in rock and fluid properties were realized through various case studies. In the absence of system/model mismatch the OC approach was seen to have a better performance than SOC as expected. The difference is not significant however; the loss recorded by SOC was only 0.26% for the simplistic reservoir size and 0.11% for the real case. With introduction of uncertainty of various forms and degree into the system which includes uncertainty in permeability, porosity, size, geometry, structure and shape of relative permeability curves, the developed feedback approach performed extremely well. The relative performance of SOC method was observed to increase with the degree of uncertainty considered in the system. In most of the cases studied, the shape of the injection trajectories found by SOC approach resemble those of the BM despite the presence of uncertainties, a situation that led to finding optimum oil and water production profiles, hence close to optimal NPVs.

Uncertainty is not considered in the formulation of the CVs due to complexity of oil reservoir, the robustness of the CVs is therefore entirely due to the feedback nature of the SOC strategy. With introduction of uncertainties in the CV formulation, the performance of the technique can be improved further.

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Reference

Brouwer, D.R., Jansen, J.-D., 2004. Dynamic Optimization of Waterflooding with Smart Wells using Optimal Control Theory. SPE *J. Pap*. 9, 391–402.

Fotiou, I.A., Rostalski, P., Parrilo, P.A., Morari, M., 2006. Parametric Optimization and Optimal Control using Algebraic Geometry Methods. *Int. J. Control* 79, 1340–1358.

Gangping, L., Jun, H., 2011. Iterative Learning Control for Batch Processes Based on Support Vector Regression Model with Batchwise Error Feedback. Presented at the The 2nd International Conference on Intelligent Control and Information Processing (ICICIP 2011), *IEEE*, Harbin, China, pp. 952–955. doi:978-1-4577-0816-9/11/$26.00

Grema, A.S., 2014. Optimization of Reservoir Waterflooding (PhD). Cranfield University, U.K., Cranfield, Bedfordshire.

Grema, A.S., Cao, Y., 2016. Optimal Feedback Control of Oil Reservoir Waterflooding Processes. *Int. J. Autom. Comput*. 13, 73–80. doi:10.1007/s11633-015-0909-7

Grema, A.S., Cao, Y., 2013. Optimizaton of Petroleum Reservoir Waterflooding using Receding Horizon Approach. Presented at the 2013 IEEE 8th *Conference on Industrial Electronics and Applications (ICIEA)*, Melbourne, Australia, pp. 397–402.

Grema, A.S., Landa, A.C., Cao, Y., 2015. Dynamic Self-Optimizing Control for Oil Reservoir Waterflooding. Presented at the 2nd IFAC Workshop on Automatic Control in Offshore Oil and Gas Production, Florianopolis, Brazil, pp. 50–55.

Grema, A.S., Mohammed, H.I., Girei, S.A., Grema, M.B., 2016. Optimization of Smart Wells using Optimal Control Theory. *J. Robot. Mechatron. Syst.* 1, 29–36.

Pastorino, M., 2007. Stochasic Optimization Methods Applied to Microwave Imaging: A Review. *IEEE Trans. Antennas Propag.* 55, 538–548. doi:10.1109/TAP.2007.891568

van Essen, G.M., Van den Hof, P., Jansen, J.-D., 2013. A Two-Level Strategy to Realize Life-Cycle Production Optimization in an Operational Setting. *SPE J*. 1057–1066. doi:10.2118/149736-PA

Yeten, B., Durlofsky, L.J., 2003. Optimization of Nonconventional Well Type, Location, and Trajectory. *SPE J. Pap*. 200–210.