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A Two-Level Strategy to Realize Life-Cycle Production Optimization in an Operational Setting

G.M. van Essen, SPE, P.M.J. Van den Hof, and J.D. Jansen, SPE, Delft University of Technology

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Abstract

We present a two-level strategy to improve robustness against uncertainty and model errors in life-cycle flooding optimization. At the upper level, a physics-based large-scale reservoir model is used to determine optimal life-cycle injection and production profiles. At the lower level these profiles are considered as set points (reference values) for a tracking control algorithm, also known as a model predictive controller (MPC), to optimize the production variables over a short moving horizon based on a simple data-driven model. We used a conventional reservoir simulator with gradient-based optimization functionality to perform the life-cycle optimization. Next, we applied this optimal strategy to a set of reservoir models with markedly different geological characteristics. We compared the performance (oil recovery) of these models when applying the life-cycle strategy with and without the corrections provided by the data-driven algorithm and the tracking controller. In this theoretical study we observed that the use of the lower-level controller enabled successful tracking of the reference values provided by the upper-level optimizer. In our example, a performance drop of 6.4 % in net present value, caused by differences between the reservoir model used for life-cycle optimization and the (synthetic) true reservoir, was successfully reduced to only 0.5% when applying the two-level strategy. Several studies have demonstrated that model-based life-cycle production optimization has a large scope to improve long-term economic performance of water flooding projects. However, because of uncertainties in geology, economics and operational decisions, such life-cycle strategies cannot simply be applied in reality. Our two-level approach offers a solution to realize the theoretical potential of life-cycle optimization in a more operational setting.

Introduction

Several studies have shown that there is considerable scope to improve reservoir management by using reservoir models for the optimization of economic life-cycle performance. This type of model-based life-cycle optimization is also referred to as ‘flooding optimization’, ‘recovery optimization’, ‘sweep optimization’, or ‘production optimization’, although the latter name is conventionally reserved for more short-term operational optimization without the use of a reservoir simulation model. A very efficient way to perform model-based life-cycle optimization is with the aid of gradient-based methods where the gradient is obtained through an adjoint technique; see e.g. Asheim (1988), Sudaryanto and Yortsos (2000), Brouwer and Jansen (2004), Sarma et al. (2005), or Kraaijevanger et al. (2007). For further references we refer to the recent review paper by Jansen (2010). Alternative methods, which are generally less efficient but much easier to implement, use a variety of methods such as streamline techniques (Alhuthali et al. 2007), evolutionary techniques (Almeida et al., 2007), stochastic techniques (Wang et al. 2009), ensemble techniques (Su and Oliver, 2010) or gradient free optimization methods (Echeverría Ciaurri et al., 2011). In all these studies the objective function is typically ultimate recovery or net present value (NPV) while the controllable input is a set of well controls in the form of prescribed bottom hole pressures, flow rates or valve settings. In practice the optimal inputs, as obtained from the optimization, cannot be directly applied in production operations because:

1) There is a very large uncertainty in reservoir flow parameters, and the real reservoir response will always be different from the simulated response.

2) The optimal inputs, in terms of life-cycle economic performance, are often suboptimal during the early phase of reservoir production in terms of instantaneous production rates.

3) The optimal inputs (rates, bottom hole pressures) are often impractically frequently varying in time.

4) Reservoir simulation models are usually much too coarse to represent near-well bore reservoir dynamics such as gas or water coning.

5) Unforeseen operational activities such as breakdown maintenance or well interventions cannot be accounted for in the reservoir simulator.

To a certain extent limitation 1), i.e. the effect of uncertainties in the reservoir flow parameters, can be counteracted by performing the optimization in a 'robust' fashion using an ensemble of reservoir models; see e.g. van Essen et al. (2009). A further step to counteract uncertainties is through frequent model updating with the aid of computer-assisted history matching (CAHM). Such a combination of life-cycle optimization and CAHM is sometimes called 'closed-loop reservoir management' or 'closed-loop' production optimization', and we refer to e.g. Naevdal et al. (2006), Sarma et al. (2008), Chen et al. (2008), Jansen et al. (2009) and Wang et al. (2009) for further information. Limitation 2), i.e. the sub-optimal nature, from a production perspective, of 'optimal' life-cycle settings can to a certain extent be alleviated by sequential optimization or multi-objective optimization; see e.g. Van Essen et al. (2011). However, limitations 3) to 5) still make direct operational use of reservoir-model based inputs practically impossible.

Multi-level optimization and control

Similar difficulties to practical implementation of long-term optimal control strategies occur in the process industry and the standard solution is to use a multi-level control structure in which the results of a higher lever serve as optimal reference for the next lower level. Similar structures have been proposed by e.g. Saputelli et al. (2006) and Foss and Jensen (2010) for use in upstream oil and gas operations. The latter paper describes a four-level structure that makes a distinction between 'asset management', 'reservoir management', 'production optimization' and 'control and automation'. Here we consider the second and the third level. At the second level we combine the use of model-based optimization and CAHM (and possibly classic surveillance techniques) to perform closed-loop reservoir management in the reservoir engineering domain. At the third level we propose the use of relatively simple data driven models in combination with a control algorithm to determine well settings in the production optimization domain. We note that in similar control structures in the process industry the second and third levels are often referred to as dynamic real-time optimization (D-RTO) and model predictive control (MPC) respectively.

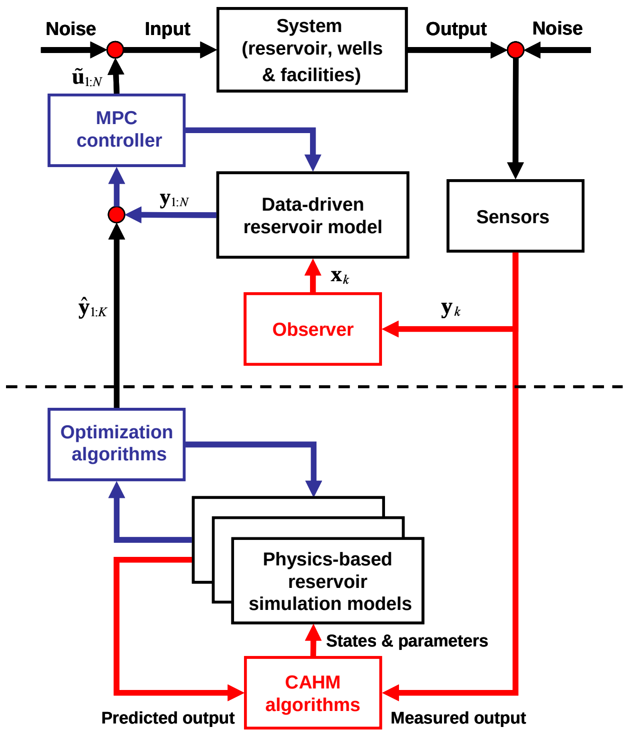

Fig. 1: Two-level strategy to combine closed-loop reservoir management (bottom part of the figure) with model predictive control of production (top part of the figure).

Fig. 1 represents a schematic of our proposed two-level strategy. The box at the very top of the figure represents the 'real world', i.e. the system consisting of reservoir, wells and facilities. The boxes at the bottom of the figure (below the dotted line) represent reservoir simulation models and additional CAHM and life-cycle optimization tools to perform long-term closed-loop reservoir management. This bottom part of the figure is identical to the schematic presented in e.g. Jansen et al. (2009). The other boxes, above the dotted line, represent elements of the model-predictive production control. Their meaning will be described in detail below.

Reservoir Modeling using Linear Data-Driven Models

The introduction of advanced (subsurface) production measurement devices in new wells has opened the way for data-driven modeling techniques. The measurement frequency of these devices is quite high (in the order of seconds to minutes) in relation to the time step size of physics-based reservoir simulation models (in the order of days to months). Before the data are assimilated into these simulation models, they are therefore resampled and post-processed to match the time step size, by which all information on fast, localized dynamics is lost. However, using the high-resolution data in data-driven modeling, the fast dynamics are captured such that short-term predictions are better, compared to those of physics-based reservoir models. There exists a wide variety of data-driven modeling methods that create a model based on the input and output data it has been given, e.g. neural networks, genetic algorithms or polynomial interrelations. Early attempts to apply data driven modeling techniques to hydrocarbon reservoirs have been described by Rowan and Klegg (1963) and Chierici et al. (1981), while more recent attempts include extended Kalman filtering (Liu et al., 2009) and capacitance-resistance modeling (Sayarpour et al., 2009). We use a so-called 'system identification' technique to determine a linear data-driven model. System identification, which has its origins in the downstream oil industry, is a black-box method, i.e. it creates a model solely based on measured data (Ljung, 1987). The order of the (linear) model, i.e. the number of dominant dynamic degrees of freedom represented in the identified model, is inferred from the data itself. During the modeling process the order of the model is increased until the residual error between modeled and measured data shows no evidence of uncaptured dynamics. In the example presented in this paper, a special sub-class of system identification has been used known as 'subspace identification' (SubID). Subspace identification was used because of its simple structure, which is well suited for multiple input – multiple output (MIMO) systems, and because of its computational efficiency. For a detailed description of the method, which is beyond the scope of this paper, we refer to Viberg (1995) and Van Overschee and De Moor (1996). For earlier applications to reservoir modeling, see Markovinović et al. (2002) and Heijn et al. (2004). The data-driven model determined through SubID was subsequently used as prediction model for the model predictive controller. In the example described in this paper we consider a reservoir with eight water injection wells and four production wells, each equipped with devices to measure total flow rates and down hole pressures. We chose an input vector with twelve elements:

$$\mathbf{u} = \begin{bmatrix} u_1 & u_2 & \cdots & u_{12} \end{bmatrix}^T = \begin{bmatrix} p_{wf,1} & p_{wf,2} & p_{wf,3} & p_{wf,4} & \vdots & q_{wi,5} & q_{wi,6} & \cdots & q_{wi,12} \end{bmatrix}^T , \quad (1)$$

where $p_{wf,1},\ldots,p_{wf,4}$ represent the bottom hole pressures in the producers, and $q_{w,9},\ldots,q_{w,12}$ are the flow rates in the injectors. The output vector was chosen as

$$\mathbf{y} = \begin{bmatrix} y_1 & y_2 & y_3 & y_4 \end{bmatrix}^T = \begin{bmatrix} q_{t,1} & q_{t,2} & q_{t,3} & q_{t,4} \end{bmatrix}^T , \quad (2)$$

where the four elements $q_{t,1},\ldots,q_{t,4}$ are the total flow rates (i.e. the sum of oil and water rates) in the producers. As mentioned above, the identified model has degrees of freedom, the number of which determines the order of the model, and which can be represented as state variables **x**, linearly related to the inputs **u** and the outputs **y**. Unlike in a physics-based reservoir simulation model, where the state variables are pressures, saturations or component concentrations, the states in an identified model do not have a direct physical interpretation. To capture all relevant dynamics in the identified model, the input **u** must be persistently exciting during the length of the identification experiment, meaning that all relevant reservoir dynamics need to be stimulated by the inputs (Ljung, 1987). Design of such an experiment, in terms of the amplitude, frequencies and length of the input **u** can be done on the basis of a physics-based large-scale reservoir simulation model and subsequently applied to the real reservoir. This approach was conceptually also adopted in the example presented in this paper, although we used a synthetic 'truth' in the form of a second, more detailed, reservoir simulation model.

Model Predictive Control in Water Fooding

The model predictive controller, as indicated in Fig. 1, acts as a tracking controller for the reference variables obtained from the life-cycle optimization based on a frequently updated reservoir model. As usual, the life-cycle optimization aims at maximizing NPV defined as an economic objective function J which for our example becomes

$$J = \sum_{k=1}^{K} \left[\frac{\sum_{i=1}^{8} r_{wi} \cdot \left(q_{wi,i}\right)_k + \sum_{j=1}^{4} \left[r_{wp} \cdot \left(q_{wp,j}\right)_k + r_o \cdot \left(q_{o,j}\right)_k \right]}{(1+b)^{\frac{t_k}{\tau_t}}} \cdot \Delta t_k \right], \tag{3}$$

where $k = 1, 2, \ldots, K$ are the time steps in the simulator, $q_{wi,i}$ are the water injection rates of well i, $q_{wp,j}$ are the water production rate of well j, $q_{o,j}$ are the oil production rate of well j, r_{wi} are the water injection costs, r_{wp} are the water production costs, r_o is the oil revenue, Δt_k is the time interval of time step k, and b is the discount rate (expressed as a fraction) for a reference time τ_t. During the optimization procedure, the input vectors $\mathbf{u}_{1:K}$ are iteratively changed until a maximum value of J is obtained. (The notation $\mathbf{u}_{1:K}$ indicates the set of input vectors over the entire simulation period: $\mathbf{u}_{1:K} = \{\mathbf{u}_1, \mathbf{u}_2, \ldots \mathbf{u}_K\}$). Usually the optimal input vector $\hat{\mathbf{u}}_{1:K}$ (where the hat indicates optimality) is the desired result of the life-cycle optimization procedure. Here, however, we choose the corresponding optimal output $\hat{\mathbf{y}}_{1:K}$ as the results and use this set of optimal total flow rates as the reference variables for the model-predictive controller. The controller now attempts to find corrected inputs $\tilde{\mathbf{u}}$ such that the difference between the actual measured outputs $\mathbf{y}$ and the optimal outputs $\hat{\mathbf{y}}$ is minimal. This is achieved by minimizing the following objective function over a relatively short time horizon:

$$V\left(\tilde{\mathbf{u}}_{1:N}\right) = \sum_{k=1}^{N} \left(\mathbf{y}_{k+1} - \hat{\mathbf{y}}_{k+1}\right)^T \mathbf{W}_1 \left(\mathbf{y}_{k+1} - \hat{\mathbf{y}}_{k+1}\right) + \left(\tilde{\mathbf{u}}_k - \hat{\mathbf{u}}_k\right)^T \mathbf{W}_2 \left(\tilde{\mathbf{u}}_k - \hat{\mathbf{u}}_k\right), \tag{4}$$

where N is the number of time steps over the control horizon, and $\mathbf{W}_1$ and $\mathbf{W}_2$ are weighting matrices. The second term at the right-hand side of equation (2) ensures that the corrected input $\tilde{\mathbf{u}}$ does not deviate too much from the optimal input $\hat{\mathbf{u}}$ as computed in the life-cycle optimization step. The prediction of the output $\mathbf{y}_{1:N}$ over the control horizon is performed with the aid of the identified model. Because the SubID method results in a model with a (small) number of internal state variables $\mathbf{x}$, it is necessary to specify initial conditions $\mathbf{x}_0$ at the start the minimization of V. These can be estimated from the known inputs $\tilde{\mathbf{u}}$ and the measured outputs $\mathbf{y}$ with the aid of a so-called state estimator. Further details of the identification and MPC procedures will be discussed in the example below. It should be noted that because, in our example, the number of inputs is twice the number of outputs, the minimization problem may become ill-posed. Only part of the control input $\tilde{\mathbf{u}}_{1:N}$ will then be implemented after which the process from state estimation to application of $\tilde{\mathbf{u}}$ is repeated. As the real reservoir moves away from the state it was in when the linear data-driven model was created, the prediction accuracy of the model will decrease and re-identification is required. In doing so, the benefit of improved prediction accuracy must be evaluated against the drop in tracking performance during the experiment. However, how to determine the best instant to initiate another re-modeling experiment is not explored in this work, but will be the subject of future research.

Example

The reservoir considered in our example is depicted in **Fig. 2**. Its geological structure involves a network of meandering high-permeable channels. The remaining reservoir properties can be found in **Table 1**. The life-cycle of the reservoir covers a period of 11.5 years. Of this reservoir a large-scale model was created to serve as the synthetic 'truth'. In order to provide realistic predictions of short-term dynamic behavior of the reservoir, a very fine spatial discretization around the wells was adopted and a (relatively) very short time step size was chosen of 0.25 days. However, neither artificial measurement noise nor disturbances were applied to the synthetic model or its synthetic input/output data. A second reservoir model was created which serves as the model to perform life-cycle optimization and design the identification experiment. No grid refinement around the wells was used and a time step size of 30 days was adopted. Besides the coarser discretization in space and time, the second model deviates from the 'truth' in its geological structure. In particular it has channels in a different flow direction, such that different wells are inside the high-perm streaks; see Fig. 2. We used a fully implicit in-house reservoir simulator.

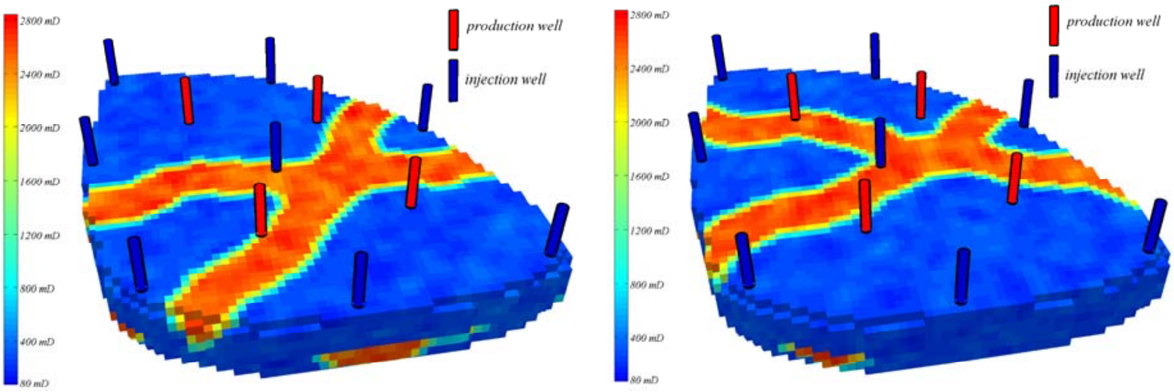

Fig. 2: (left) 3D reservoir model, used as synthetic 'truth', with 8 injection wells and 4 production wells. Its geological structure involves a network of meandering channels of high permeability. The model to the right is used for life-cycle optimization and differs from the model to the left in the direction of the channels, the absence of grid refinement and the larger time step size of 30 days.

TABLE 1 – GEOLOGICAL AND FLUID PROPERTIES FOR EXAMPLE

property	value	units
ϕ	0.20	-
ρ_o (@1 bar)	800	kg/m^3
ρ_w (@1 bar)	1000	kg/m^3
c_o	$15 \cdot 10^{-5}$	1/bar
c_w	$4 \cdot 10^{-5}$	1/bar
μ_o	$4 \cdot 10^{-3}$	Pa s
μ_w	$1 \cdot 10^{-3}$	Pa s
p_{cow}	0	bar
S_{wc}	0.20	-
S_{or}	0.05	-
k_{ro}	0.80	-
k_{rw}	0.92	-
n_o	4.75	-
n_w	3.00	-

Economic Life-Cycle Optimization

In the control structure as shown in Fig. 1, the optimal (reference) output $\hat{\mathbf{y}}_{1:K}$ is determined by the life-cycle optimizer using objective function (3). We used oil revenues r_o equal to 56.6 \$/m^3, water production costs r_{wp} of 6.3\$/m^3, zero water injection costs, and an annual discount rate b equal to 0.1. We solved the life-cycle optimization problem with the aid of a gradient-based algorithm for which the gradients were obtained with the adjoint formalism in the simulator (Kraaijevanger et al., 2007). We applied rate constraints to the injectors (a maximum rate of 1,590 m^3/day) and pressure constraints to the producers (a minimum bottom hole pressure of 375 bar, i.e. 25 bar below the initial reservoir pressure). We did not apply any CAHM to update the model, nor did we use multiple models to reduce the sensitivity to geological uncertainties. Therefore the only way to counteract the negative effects of model inaccuracies on the life cycle performance of the 'true' reservoir is through the actions of the model predictive controller. Solving the life-cycle optimization problem resulted in an expected maximum NPV of 596×10^6 \$.

System Identification

System identification was performed on the 'true' reservoir. The inputs were the water injection rates of the eight injectors and the bottom-hole pressures of the four producers. The water flooding process is non-linear and as a result the prediction accuracy of a linear model will decrease when the prediction horizon increases. However, in this first experiment, we only once identified a linear model at the start of production for simplicity reasons. The duration of the experiment was chosen using the rule of thumb that the length should be minimal five times the largest time constant. Through step response analysis on the reservoir model (i.e. not on the 'truth'), the largest time constant was estimated and the minimal duration of the experiment was estimated at 75 days. For the inputs q_{wi} and p_{wf} to the 'real' reservoir, random binary signals (RBS) were generated. RBS signals were used in this experiment because they cover a wide spectrum of frequencies, which makes them suitable to generate a persistently exciting input. From step responses on the reservoir model for each input, it was found that the response to changes in q_{wi} were much slower than responses to changes in p_{wf}. In order to amplify the low frequency content of excitation signal of the injection rates, the clock period of the RBS signal was set to three sample times (of 0.25 days). The amplitudes of the RBS signals were set to 1,590 m^3/day and 1 bar for q_{wi} and p_{wf} respectively, using the reservoir model to determine that the effect on the outputs was significant.

In order to maintain good economic performance, the RBS signals with zero mean were superimposed upon the preferred inputs which were taken equal to $\hat{\mathbf{u}}$. However, whenever addition of the RBS signal led to infeasibility with respect to the well constraints, the mean value was moved up or down until feasibility was restored. In the identification experiment, the first 25 days of data were omitted after which all initialization effects had died out. The excitation signals and the optimal inputs $\hat{\mathbf{u}}$ can be observed in **Fig. 3**. The sampling frequency of the measured outputs $\mathbf{y}$ is determined by the time step size of the 'truth model', which in this example was equal to 0.25 days. The identification experiment was conducted in open-loop, since the depletion process is inherently stable. Based on these data, an 8th-order SubID model was identified. **Fig. 4** shows the model fit of the model with respect to the measured output data for all four producers. It can be observed that the output of the identified model has satisfying accuracy.

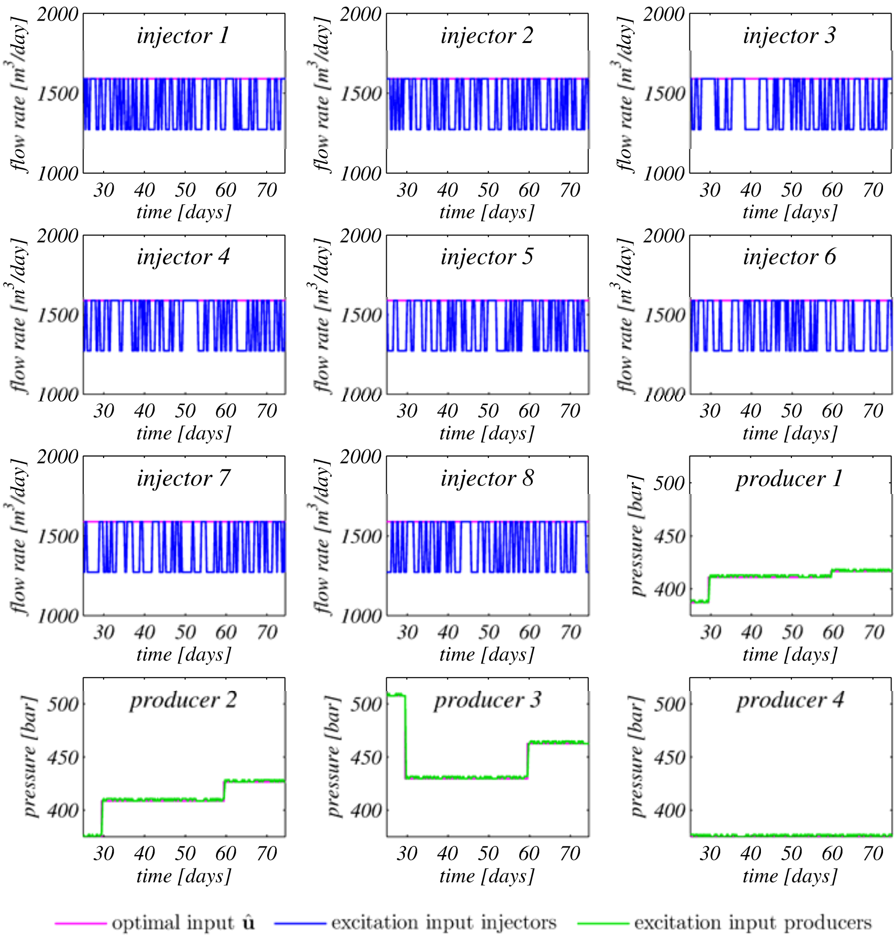

Fig. 3: Excitation signal for the identification experiment along with optimal inputs $\hat{\mathbf{u}}$ for each input.

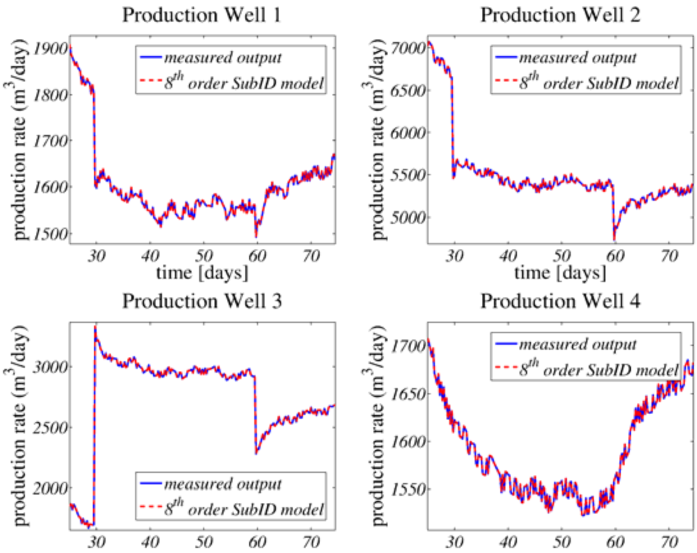

Fig. 4: Model fit of the 8th-order SubID model with respect to the measured output data.

Model Predictive Control

MPC involves minimization of a cost function as described by equation (4). The desired input was chosen equal to $\hat{\mathbf{u}}_{1:K}$ as a best guess to maximize economic life-cycle performance. Weighting matrix $\mathbf{W}_1$ was taken equal to unity. Weighting matrix $\mathbf{W}_2$ was used only to weigh deviations of the injection rates q_{wi} from optimal inputs $\hat{\mathbf{u}}_{1:K}$, such that tracking is mainly realized through changes in the bottom-hole pressures p_{wf} of the production wells. The nonzero elements of $\mathbf{W}_2$ were chosen equal to unity. In this experiment, the prediction horizon N was chosen equal to 28, i.e. to one week. Each time step, the minimization problem is solved for the (moving) prediction horizon, which involves two sequential steps: State estimation and quadratic programming (QP).

1. *State Estimation*. In this simulation study, no artificial noise was added to the measurements. As a result, the state estimation problem can be attacked quite straightforwardly using a Luenberger observer (Friedland, 1986). Note however that alternative choices for state estimation may be considered, e.g. Kalman filtering.

2. *Quadratic Programming*. To solve the minimization of objective function V subject to the inequality constraints on the inputs, a QP problem needs to be solved. In this experiment, a custom made QP solver was used, implemented in the in-house reservoir simulator.

The controls $\tilde{\mathbf{u}}_{1:N}$ as determined by the MPC controller were re-calculated and applied to the 'real' reservoir at every 0.25 day time step; see **Fig. 5**.

Results

We compare the results from inputs $\tilde{\mathbf{u}}$ obtained with the additional MPC layer to results from direct, open-loop application of optimal inputs $\hat{\mathbf{u}}$. Performance is both evaluated in terms of tracking performance and NPV. Tracking performance can be observed in **Fig. 6**. In **Table 2**, the NPVs of the open-loop application of $\hat{\mathbf{u}}$ and $\tilde{\mathbf{u}}$ are shown in comparison to the expected maximum NPV determined by the life-cycle optimizer. Fig. 6 depicts the reference and output trajectories for both the open-loop and the MPC controlled case for each of the four production wells over the life of the field. In each of the four plots, four different stages can be identified. In the first 75 days of production, the identification experiment is conducted where the optimal inputs $\hat{\mathbf{u}}$ serve as mean values. During this period the error is large because of the model error between the reservoir model and the 'truth', while the MPC controller is not active yet. From 75 days to approximately 500 days tracking performance is good due to activation of the MPC controller. After 500 days tracking performance decreases, however still outperforming open-loop control. This drop is the result of water breakthrough in the production wells, which has a strong nonlinear effect of the dynamics. After approximately 3,000 days tracking improves again, due to the fact that mainly water is produced resulting in a more linear response to the inputs.

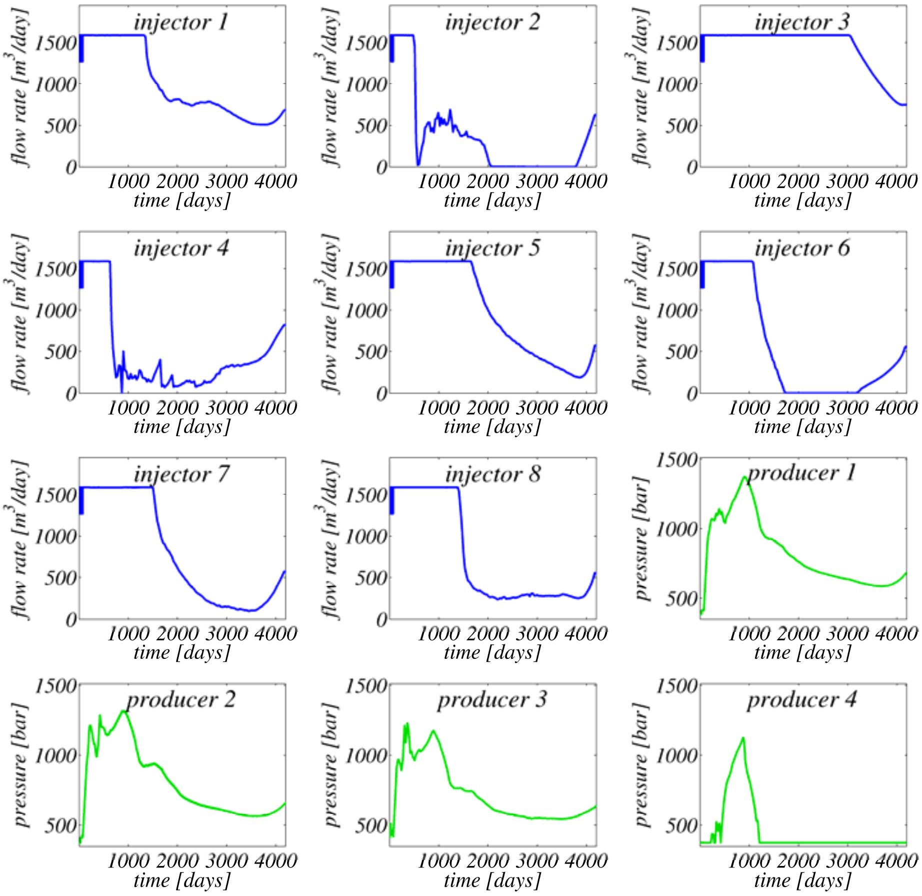

Fig. 5: Controls $\tilde{\mathbf{u}}$ as determined by the MPC controller.

Conclusions

The introduction of a two-level optimization and control strategy as described in our paper, combining life-cycle optimization with MPC (tracking control), was aimed at attenuation of geological and operational uncertainties and the effect of model errors. Based on the example considered we conclude that

- It is possible, from a system-theoretical point of view, to obtain a linear data-driven reservoir model through system identification methods, which gives accurate predictions for a time horizon that is relatively short, but long enough to realize MPC control.
- The results of reference tracking through MPC are promising. However, even better results are expected when frequent re-estimation of the linear data-driven model is conducted over the length of the field's life-cycle.

It should be noted that the combination of life-cycle optimization and tracking control using MPC can quite easily be combined with alternative methods that are aimed at counteracting the negative effects of uncertainty on economic performance, such as the robust optimization or the addition of CAHM as in closed-loop reservoir management.

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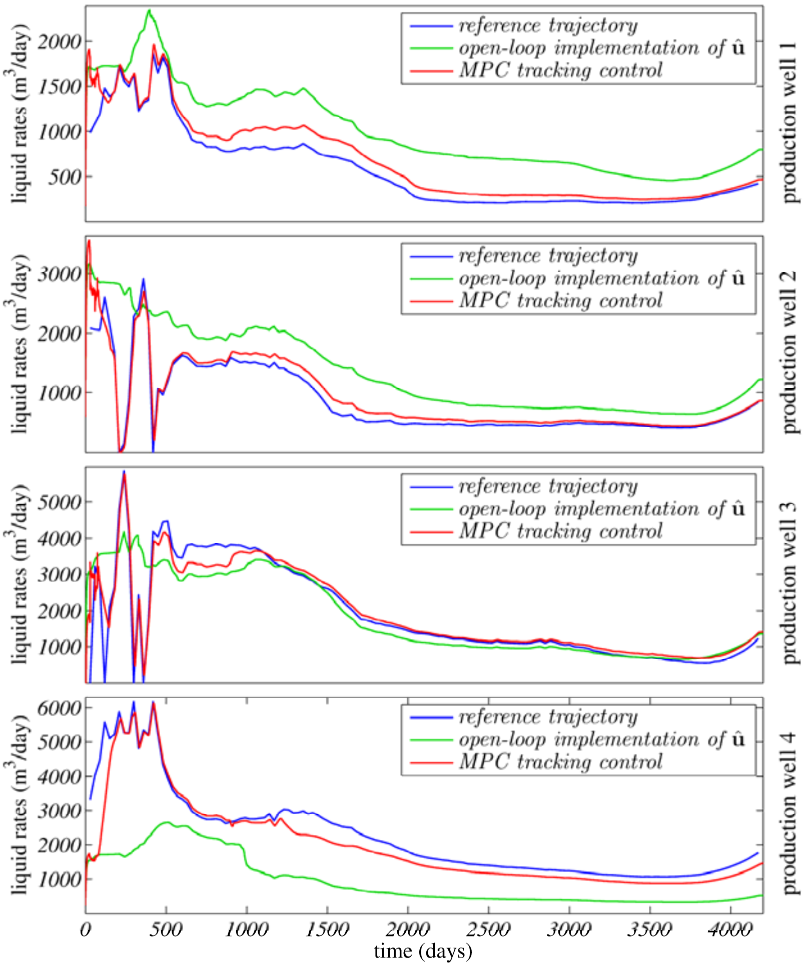

Fig. 6: Reference and output trajectories for the open-loop application and the MPC controlled case for each of the four production wells over the life of the field.

TABLE 2 – Economic Performance		
	NPV	% change
Maximum predicted	596×10^6 \$	-
Open-loop application of $\hat{\mathbf{u}}$	558×10^6 \$	-6.4%
MPC control using $\tilde{\mathbf{u}}$	594×10^6 \$	-0.5%

Nomenclature

b = discount rate, t^{-1}, 1/year
c = compressibility, m^{-1} L t^2, 1/bar
J = objective function, \$
k = discrete time, or permeability, L^2, mD
K = total number of time steps
n = Corey exponent
p = pressure, m L^{-1} t^{-2}, Pa
q = flow rate, m^3/d
r = unit revenue/cost, \$/m^3
S = saturation
t = time, t, d
$\mathbf{u}$ = input vector
$\mathbf{x}$ = state vector

y = output vector
V = objective function
W = weight matrix
μ = viscosity, m L^{-1} t^{-1}, Pa s
ρ = density, L^{-3} m, kg/m^3
τ = reference time, t, d
ϕ = porosity

Subscripts
cow = capillary (oil/water)
ro = relative, oil
rw = relative, water
t = total
o = oil
wf = flowing well bore
wi = injected water
wp = produced water

Superscripts
T = transposed

Glossary
CAHM = computer-assisted history matching
D-RTO = dynamic real time optimization
MIMO = multiple input – multiple output
MPC = model predictive control
NPV = net present value
QP = quadratic programming
RBS = random binary signal
SubID = sub space identification

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