SPE 119098

Closed-Loop Reservoir Management

J.D.Jansen, SPE, Shell Intl. E&P (SIEP) and Delft University of Technology (DUT); S.D. Douma, SPE, D.R. Brouwer, SPE, SIEP; P.M.J. Van den Hof, O.H. Bosgra and A.W. Heemink, DUT.

This paper was prepared for presentation at the 2009 SPE Reservoir Simulation Symposium held in The Woodlands, Texas, USA, 2–4 February 2009.

Abstract

Closed-loop reservoir management is a combination of model-based optimization and data assimilation (computer-assisted history matching), also referred to as 'real-time reservoir management', 'smart reservoir management' or 'closed-loop optimization'. The aim is to maximize reservoir performance, in terms of recovery or financial measures, over the life of the reservoir by changing reservoir management from a periodic to a near-continuous process. The key sources of inspiration for our work are measurement and control theory as used in the process industry and data assimilation techniques as used in meteorology and oceanography. We present results of a numerical example to illustrate the scope for closed-loop water flooding using real-time production data under uncertain reservoir conditions. The example concerns a 12-well water flood in a channelized reservoir. Optimization was performed using a reservoir simulator with functionality for adjoint-based life cycle optimization under rate and pressure constraints. Data assimilation was performed using the ensemble Kalman filter. Applying an optimization frequency of respectively once per 4 years, once per 2 years, once per year and once per 30 days resulted in an increase of net present value (NPV) with 6.68, 8.29, 8.30 and 8.71% compared to a conventional reactive control strategy. Moreover, the results for the 30-day cycle were very close (0.15% lower NPV) to those obtained by open-loop optimization using the 'true' reservoir model. We illustrate that for closed-loop reservoir management with a fixed well configuration, the use of considerably different reservoir models may lead to near-identical results in terms of NPV. This implies that in such cases the essential information may be represented with a much less complex model than suggested by the large number of grid blocks in typical reservoir models. We also illustrate that the optimal rates and pressures as obtained by open- or closed-loop optimization are often too irregular to be practically applicable. Fortunately, just as is the case for the data assimilation problem, the flooding optimization problem usually contains many more control variables than necessary, allowing for optimization of long-term reservoir performance while maintaining freedom to perform short-term production optimization.

Introduction

Our work aims at increased reservoir performance, in terms of recovery or financial measures, using a measurement and control approach to reservoir management. This idea has been around for many years in different forms, often centered around attempts to improve reservoir characterization from a geosciences perspective; see e.g. Chierici (1992). Moreover, recently 'closed-loop' or 'real-time' approaches to hydrocarbon production have received growing attention as part of various industry initiatives with names as 'smart fields', 'i-fields', 'e-fields', 'self-learning reservoir management' or 'integrated operations'; see Jansen et al. (2005) for some further references. However, whereas the focus of most of these initiatives is primarily on optimization of short-term production, in our work we concentrate on life-cycle optimization, i.e. on processes at a timescale from years to tens of years. We perform reservoir flooding optimization, based on numerical simulation models, in combination with frequent model updating through data assimilation (computer-assisted history matching). This approach has lately also been referred to as 'closed-loop reservoir modeling' or 'closed-loop production optimization' and some recent references will be discussed below. In contrast to the geosciences-focused approach, we emphasize the need to focus on those elements of the modeling process that can both be verified from measurements and that bear relevance to controllable parameters such as well locations or, in particular, production parameter settings. The underlying hypothesis is that

> *"It will be possible to significantly increase life-cycle value by changing reservoir management from a batch-type to a near-continuous model-based controlled activity."*

The term “significantly” may be understood in statistical sense, i.e. referring to a formal hypothesis test based on multiple experiments. Alternatively, it may be understood more pragmatically as “large enough to be of practical value”. We stress that, in our view, “closed-loop” does not imply removal of human judgment from the loop. The use of model-based optimization and data assimilation techniques should result in a reduction of time spent on repetitive and tedious human activities and thus in more time to be spent on judging results and taking decisions.

Key elements

Fig. 1 displays the key elements in the closed-loop reservoir management process. The top of the figure represents the physical system consisting of reservoirs, wells and facilities. The center of the figure displays the system models which may include static (geological), dynamic (reservoir flow) and well bore flow models. Typically we need multiple models, each having uncertain parameters, to quantify the large uncertainty in our knowledge of the subsurface. At the right of the figure we find the sensors that keep track of the processes that occur in the system. These may be thought of as real sensors measuring production variables such as wellhead pressures or phase rates, either through production tests or on-line multi-phase flow meters, or ‘soft-sensors’ that measure production data indirectly. However we may also interpret the sensors more abstractly as sources of information about the system variables, e.g. interpreted well tests, time-lapse seismics or other surveillance data. At the left we find the optimization algorithms, indicated by a blue box and arrows. Again these may be interpreted as actual algorithms for production optimization influencing e.g. wellhead choke settings or injection rates, but also more abstractly as decisions in a field development plan, e.g. the choice of well positions. The state variables of the system, i.e. the pressures and saturations in the reservoirs, the pressures and phase rates in the wells, etc., are only known to a limited extent from the measured, usually noisy, output. Even more uncertain are the parameters of the system, i.e. the permeabilities and porosities, fault transmissibilities, fluid properties etc., while also the system boundaries and initial conditions are uncertain. Finally even the input to the system is only known to a limited extent; e.g. water injection rates or gas lift rates may be roughly known, but aquifer support may be a major unknown. The unknown inputs can also be interpreted as noise. Data assimilation (i.e. computer-assisted history matching) can be used to reconcile the measured output with the uncertain models to a certain extent. This is done through adapting the model parameters and model structure until the difference between measured and simulated data is minimized in some pre-defined sense, as indicated by the red box and arrows at the bottom. The two essential elements in the closed-loop reservoir management concept are therefore model-based optimization and decision making (blue loop), and model updating through data assimilation (red loop). We will describe these processes in further detail below and present an over view of specific numerical techniques in the Appendix.

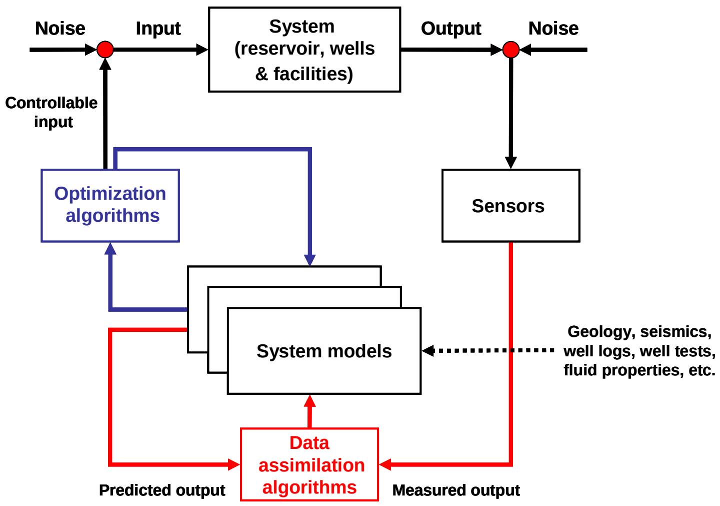

Figure 1: Key elements of the closed-loop reservoir management process.

Other elements

While optimization and data assimilation constitute the two main elements of closed-loop reservoir management, other elements may be identified which we will briefly discuss. We refer to the Appendix for references. In traditional history matching, either manually, or computer-assisted, the focus is usually on obtaining a system model that represents reality as accurate as possible. Instead, we focus on adapting our models such that they best serve to optimize the process of hydrocarbon recovery. Depending on the available level of control (e.g. a fixed well configuration versus the possibility to do infill drilling) and the available data, this may lead to more or less detailed models with more or less geological realism. In some instances the dynamics of a complex ‘high-order’ reservoir model may be accurately described with a strongly reduced number of variables. Although it may often not be possible to determine these variables a-priori, the available data and means of control may result in a relatively simple 'low-order' model for control and optimization. Simply said, it does not make sense to model more than can be identified or controlled. **Fig. 2** is an extended version of Fig. 1, which illustrates that control-relevant up- and downscaling of system models may play an important role in the closed-loop approach. This may also include reparameterization techniques to reduce the number of uncertain reservoir parameters.

Another important element is the quantification of uncertainty. This process is indicated in Fig. 2 by depicting groups of (high-order and low-order) models. They may be thought of as models based on many different geological scenarios, or as geostatistical realizations based on one or more scenarios. Uncertainty quantification requires the definition of statistical distributions for the noisy measurements and for the uncertain 'prior' model parameters, initial conditions and inputs. The next step is then to analyze their combined effect on the 'posterior' models, i.e. the models after history matching, and on the results of the life-cycle optimization based on these updated models. A full uncertainty analysis of all uncertain parameters and variables is computationally prohibitive, but various simplified analysis techniques for uncertainty quantification have been developed over the past decade, and this is an area of active research.

A further element shown in Fig. 2 is the 'virtual asset model'. This model is of course not present in real closed-loop reservoir management in which case we operate on a real asset and use real measured data. However, during the process of developing techniques for closed-loop optimization, data assimilation, scaling and uncertainty quantification, it is sometimes necessary to test them over the producing life time of the reservoir, an activity that necessarily requires a synthetic, 'virtual' asset. Another purpose of the virtual asset model is the possibility to analyze the value of measurement and control functionality. This may involve e.g. optimizing the position and the level of accuracy of sensors, or the comparison of the value of different surveillance techniques.

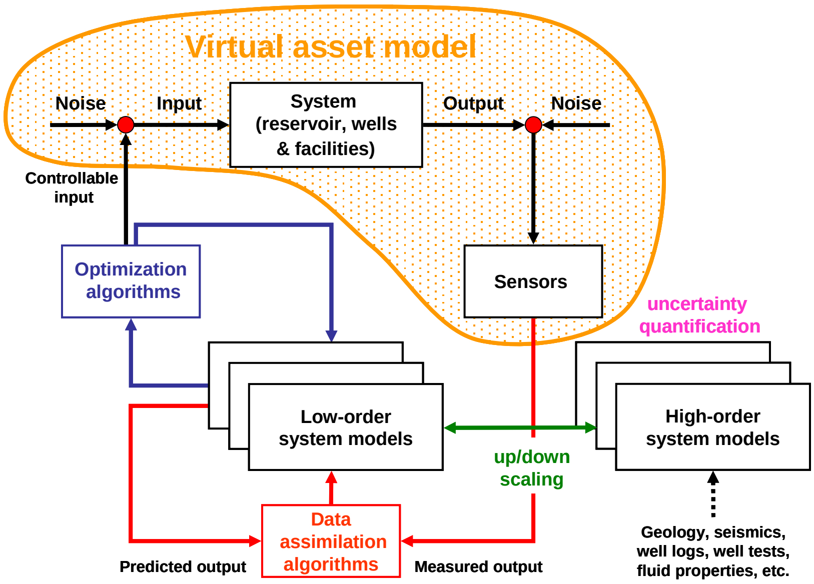

Fig. 2: Other potential elements of the closed-loop reservoir management process.

Flooding optimization and data assimilation

Notation

Vectors are indicated with bold lower case letters and matrices with bold capitals. The superscript T is used to indicate the transpose, and dots above variables to indicate differentiation with respect to time t.

Reservoir models

We consider models for multiphase flow through porous media. Starting from the governing partial differential equations for mass balance, Darcy's law, equations of state and the relevant initial and boundary conditions, and applying a semi-discretization in space (using e.g. finite differences, finite elements or finite volumes) we obtain a set of ordinary differential equations that can be expressed as (see e.g. Jansen et al., 2008)

$$\mathbf{g}\left(\mathbf{u},\dot{\mathbf{x}},\mathbf{x},\boldsymbol{\theta}\right)=\mathbf{0}\,, \tag{1}$$

where $\mathbf{g}$ is a nonlinear vector-valued function, $\mathbf{u}$ is the input vector (also called control vector), $\mathbf{x}$ is the state vector, and $\boldsymbol{\theta}$ is the vector of model parameters. In a conventional iso-thermal reservoir simulation model $\mathbf{x}$ typically contains pressures and phase saturations or component accumulations, $\mathbf{u}$ contains the well flow rates, bottom hole or tubing head pressures, or choke settings, in those grid blocks that are penetrated by wells, and $\boldsymbol{\theta}$ contains parameters like porosities, permeabilities and other reservoir and fluid properties. Using some form of time discretization, the continuous-time equation (1) can be rewritten in discrete-time form as

$$\mathbf{g}_{k+1}\left(\mathbf{u}_{k+1},\mathbf{x}_k,\mathbf{x}_{k+1}\right)=\mathbf{0} \ , \ k=0,\ldots,K-1 , \tag{2}$$

where the subscript k indicates discrete time and K is the end time. Note: We use the shortcut notation $\mathbf{x}_k$ to indicate $\mathbf{x}(t_k)$, i.e. the value of $\mathbf{x}$ at time $t=t_k$. To complete the model we need to specify initial conditions, which, in the discrete case, can be represented as

$$\mathbf{x}_0=\breve{\mathbf{x}}_0 . \tag{3}$$

Generally, we are not able to observe all state variables in the process directly. Instead, we can typically measure a number of output variables y, combined in an output vector $\mathbf{y}$, which are a function of the input variables $\mathbf{u}$ and the state variables $\mathbf{x}$ according to

$$\mathbf{y}_{k+1}=\mathbf{h}\left(\mathbf{u}_{k+1},\mathbf{x}_{k+1}\right) . \tag{4}$$

Flooding optimization

For a given configuration of wells, and in particular for a flooding scenario involving multiple injectors and producers, we can use the well rates or pressures to optimize the flooding process over the producing life of the reservoir; see e.g. Asheim (1988), Sudaryanto and Yortsos (2000), Jansen and Brouwer (2004) and Sarma et al. (2005a). As in any optimization problem, we need an objective function and constraints. For example, the objective could be to maximize the ultimate recovery or the net present value (NPV) of the water flooding process. Generally, the objective function $J(\mathbf{u}_{1:K},\mathbf{y}_{1:K})$ can be expressed as:

$$J\left(\mathbf{u}_{1:K},\mathbf{y}_{1:K}\left(\mathbf{u}_{1:K}\right)\right)=\sum_{k=1}^{K}J_k\left(\mathbf{u}_k,\mathbf{y}_k\right) , \tag{5}$$

where K is the total number of time steps, and where J_k represents the contribution to J in each time step. Note that actually all inputs up to time k may play a role in J_k as follows from recursive application of equations (2) and (4). We could therefore formally write $J_k(\mathbf{u}_k,\mathbf{y}_k(\mathbf{u}_k,\mathbf{x}_k(\mathbf{u}_{1:k})))$, but to keep the notation tractable we use $J_k(\mathbf{u}_k,\mathbf{y}_k)$ instead. An example of J_k in a typical objective function is given by

$$J_k=\left\{\frac{\sum_{i=1}^{N_{inj}}r_{wi}\left(u_{wi,i}\right)_k+\sum_{j=1}^{N_{prod}}\left[r_{wp}\left(y_{wp,j}\right)_k+r_o\left(y_{o,j}\right)_k\right]}{\left(1+b\right)^{\frac{t_k}{\tau}}}\right\}\Delta t_k , \tag{6}$$

where the control variables $u_{wi,i}$ are the water injection rates in wells $i=1,\ldots,N_{inj}$, the output variables $y_{wp,j}$ and $y_{o,j}$ are the water and oil production rates in wells $j=1,\ldots,N_{prod}$, r_{wi} and r_{wp} are the (negative valued) unit costs for water injection and water production, r_o is the unit income for oil production, and t_k and $\Delta t_k=t_{k+1}-t_k$ are the time and the time interval corresponding to time step k. The term in the denominator is a discount factor that represents the time-value of money, where b is the discount rate (cost of capital) for a reference time τ. The objective function (5) with J_k as expressed in equation (6) represents the present value of the oil produced minus the present value of the water injection and water production costs over the life of the field. Constraints can be expressed in terms of the state variables or the input variables and may be equality or inequality constraints, which we represent in a general form as

$$\mathbf{c}\left(\mathbf{u}_k,\mathbf{x}_k\right)\leq\mathbf{0} . \tag{7}$$

Typical input constraints are limits on the total water injection capacity, and typical state constraints are maximum and minimum pressures in the injection and production wells respectively. The optimization problem can now be formulated as finding the input vector $\mathbf{u}_k$ that maximizes J as defined in (5), subject to system equations (2), initial conditions (3), output equations (4) and constraints (7). Sometimes the problem is nonlinear in the inputs and the constraints, and it is nearly always nonconvex, i.e. it has multiple local maxima. Many numerical techniques are available to solve flooding optimization problems, and the Appendix gives an overview, including key references, of those that are most commonly used.

Data assimilation

Data assimilation, or computer-assisted history matching, is the adaptation of the parameters of a system model to measured data. In our case that implies updating parameters $\boldsymbol{\theta}$ using measured output data $\mathbf{d}$. Often the history matching problem is formulated as an optimization problem with an objective function defined in terms of the mismatch between measured and simulated output data; see e.g. Bennett (2002), Tarantola (2005), Evensen (2007) or Oliver et al. (2008):

$$J\left(\mathbf{y}_{1:K}\right)=\sum_{k=1}^{K}\left[\left(\mathbf{d}_k-\mathbf{y}_k\right)^T\mathbf{P}_{\eta}^{-1}\left(\mathbf{d}_k-\mathbf{y}_k\right)\right], \tag{8}$$

where $\mathbf{P}_{\eta}$ is a weight matrix which is often chosen as the inverse of the error covariance matrix of the measurements. Usually the objective function is expanded to include a term that penalizes large deviations between the updated parameter values $\boldsymbol{\theta}$ and the prior values $\breve{\boldsymbol{\theta}}$:

$$J\left(\mathbf{y}_{1:K},\boldsymbol{\theta}_{1:K}\right)=\sum_{k=1}^{K}\left[\left(\mathbf{d}_k-\mathbf{y}_k\right)^T\mathbf{P}_{y}^{-1}\left(\mathbf{d}_k-\mathbf{y}_k\right)+\left(\boldsymbol{\theta}_k-\breve{\boldsymbol{\theta}}_k\right)^T\mathbf{P}_{\theta_k}^{-1}\left(\boldsymbol{\theta}_k-\breve{\boldsymbol{\theta}}_k\right)\right]. \tag{9}$$

Often the unknown parameters $\boldsymbol{\theta}$ are chosen as the permeability values in each grid block. A natural choice for the weight matrix $\mathbf{P}_{\theta}$ is then the inverse of the covariance matrix of the prior permeability field. In a similar fashion we may take into account other parameters, such as porosity values, fault transmissibility multipliers, initial conditions or uncertain source terms (i.e. well inputs). If the prior parameters and the measurement errors are assumed to have Gaussian probability distributions and the reservoir simulator **g** and measurement operator **h** are linear, equation (9) can be interpreted in a probabilistic setting as Bayes' rule for updating a prior. The estimate that is found by minimizing equation (9) is then equivalent to a posterior that represents the mean of the probability function of the model parameters $\boldsymbol{\theta}$ conditional to the measurements; see e.g. Gavalas et al. (1976), Zhang et al. (2005) and Oliver et al. (2008) for further references. In general the amount of information that can be obtained from well data is limited, especially because the pressure propagation through a reservoir is a diffusive process; see Zandvliet et al. (2008). Sometimes it is possible to obtain areal information through the use of time-lapse seismics, which may give an indication of those reservoir areas where pressures or saturations have changed; see e.g. Skjervheim et al. (2007). However, the data obtained from production measurements and time-lapse seismics are never sufficient to fully characterize the states and parameters in a traditional reservoir flow model, and data assimilation in reservoir engineering is therefore an inherently ill-posed problem. Especially if reservoir models are used for field re-development planning, involving e.g. the drilling of new wells, geological models are essential to constrain the solution space of the data assimilation problem. The Appendix gives an overview, including key references, of the most commonly used techniques for data assimilation, and also briefly discusses some aspects of reparameterization and uncertainty quantification.

Earlier work

Simple examples

The precise techniques used for flooding optimization and data assimilation in closed-loop reservoir management are not very important and indeed different combinations have been used in studies over the past years. Our first attempts to combine flooding optimization and data assimilation were published in Brouwer et al. (2004), Overbeek et al. (2004), Jansen et al. (2005) and Naevdal et al. (2006). In 2004 an exploratory Delft/Stanford workshop on closed-loop reservoir management was held after which several papers were published in a special journal issue (Jansen et al., 2006). In our early publications we considered water flooding in simple two-dimensional (2D) virtual asset models, with the aid of an adjoint-based technique for flooding optimization and the ensemble Kalman filter (EnKF) for data assimilation (See the Appendix for further details about these techniques). We found that, in these very simple models, there was significant scope for improved ultimate recovery and reduced water production. Moreover it appeared that closed-loop optimization based on an ensemble of uncertain reservoir models can lead to results that closely approach those of open-loop optimization, i.e. results based on optimization of the 'true' reservoir represented by the virtual asset. It should be noted, however, that the examples presented in these papers were very simple, with only two phases, a horizontal two-dimensional configuration, no constraints on well bore pressures and with permeability being the only uncertain parameter.

Another early combination of optimization and data assimilation was used by Aitokhuehi and Durlofsky (2005) who combined flooding optimization with smart wells using numerically determined gradients with the probability perturbation method for data assimilation. Simple 2D reservoir models were also used by Sarma et al. (2006) to demonstrate closed-loop reservoir management. They applied adjoint-based optimal control in combination with adjoint-based data assimilation and a low-order representation of an ensemble of permeability fields. In follow-up studies they included an approximate technique to quantify uncertainty (Sarma et al., 2005b), and they demonstrated the closed-loop concept on a 3D, 40,000 active-grid-block model, based on a real reservoir, and with realistic well constraints (Sarma et al., 2008). Also for the latter case it was found that there is significant scope for increasing the net present value over the producing life of the reservoir (up to 25% in this particular example) and that optimization based on an ensemble of uncertain reservoir models comes close to open-loop optimization based on the 'true' reservoir. However, it should be noted that in this example the virtual asset was chosen as one of the realizations of an ensemble of geostatistical realizations, while the remaining ensemble members were then used for the data assimilation part of the closed-loop exercise. This provides an advantage in the form of the 'correct' prior geological features being present in the ensemble used for data assimilation, a benefit that will generally not be present in a real situation.

Further simple 2D closed-loop studies were performed by Wang et al. (2007), who focused on the computational aspects of flooding optimization and provided a detailed description of the numerical experiments, and by Chen et al. (2008), who addressed systematic uncertainty quantification using ensemble-based techniques for both optimization and data assimilation.

ATW benchmark study

Recently, an SPE Applied Technology Workshop (ATW) on closed-loop reservoir management was held in Bruges, Belgium. An important feature of the workshop was the opportunity to participate in a benchmark project to test the use of flooding optimization and data assimilation methods. Results of this exercise have been reported in an overview paper; see Peters et al. (2009), and in more detail in two papers of individual participants: Chen et al. (2009) and Lorentzen et al. (2009). The benchmark project was organized in the form of an interactive competition during the months preceding the ATW, such that the results could be compared and discussed during the workshop. Participants were provided with synthetic well bore logs, 10 years of production data and interpreted 4D seismic data (in the form of coarse-scale pressure and saturation fields at year 0 and year 10) generated with a large-scale (450,000 grid block) virtual asset, the Bruges field, with a realistic reservoir geometry and structure. In addition, the participants received an ensemble of 104 reservoir models of 60,000 grid blocks each, generated using various geostatistical techniques, and assumed to be a reasonable representation of the reservoir parameters with a realistic uncertainty level. It should be noted though that the participants were also provided with deterministic 'true' data (e.g. fine-scale relative permeabilities and fluid data) which would be less well known in reality. Goal of the exercise was to maximize field performance in terms of NPV. Therefore the participants were requested to first perform a history match of the ensemble of models over the first 10 years, and then perform a life cycle flooding optimization over the remaining 20 years of producing reservoir life. Next the participants could submit their optimal production strategy for years 10 to 20 to the organizers of the benchmark study who then 'operated' the virtual asset accordingly and thus created a second set of synthetic production data. Subsequently the participants were asked to perform a second history match, this time up to year 20, and a second flooding optimization for the remaining 10 years of production, the results of which then could be returned to the organizers again to evaluate the final NPV using the virtual asset. A total of 9 participants competed using a wide variety of flooding optimization and data assimilation techniques as described in detail in Peters et al. (2006). The most successful participant achieved an NPV of 4.50×10^9 \$ which was 7.4 % higher than a reactive control strategy (4.19×10^9 \$) and close to the open-loop reference result that was obtained by the organizers through flooding optimization of the virtual asset model directly (4.63×10^9 \$, i.e. 10.5% higher than reactive control). A 'model update frequency' of once per 10 years was used in this benchmark exercise because of logistic limitations. Therefore the results do not really reflect a closed-loop reservoir management approach, but rather a traditional 'batch type' reservoir management strategy. However, the most successful participant was given the opportunity to repeat the exercise with a higher frequency (once every year) for the data assimilation and flooding optimization over years 10 to 30. This closed-loop approach indeed resulted in a small further increase in NPV in the order of 1% compared to the reactive control case. Possibly an additional increase could be achieved by using the closed-loop approach right from the start of production instead of only after year 10.

Numerical experiment

Reservoir models

In the numerical experiment reported in this paper we further investigated the hypothesis stated in the introduction, namely that "It will be possible to significantly increase life-cycle value by changing reservoir management from a 'batch-type' to a 'near-continuous' model-based controlled activity." We used a relatively small 3D two-phase (oil-water) virtual asset model of 18,553 active grid blocks of dimension 8 m×8 m×4 m, see **Fig. 3**, consisting of 7 layers as displayed in the left column of **Fig. 4**.

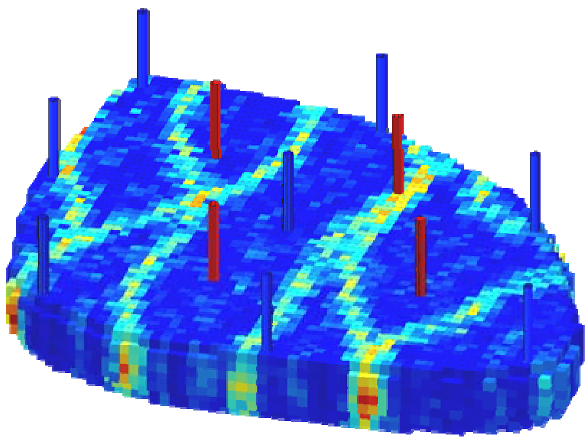

Fig. 3: Permeability field and well locations of the virtual asset; blue: injectors, red: producers (after Van Essen, 2006).

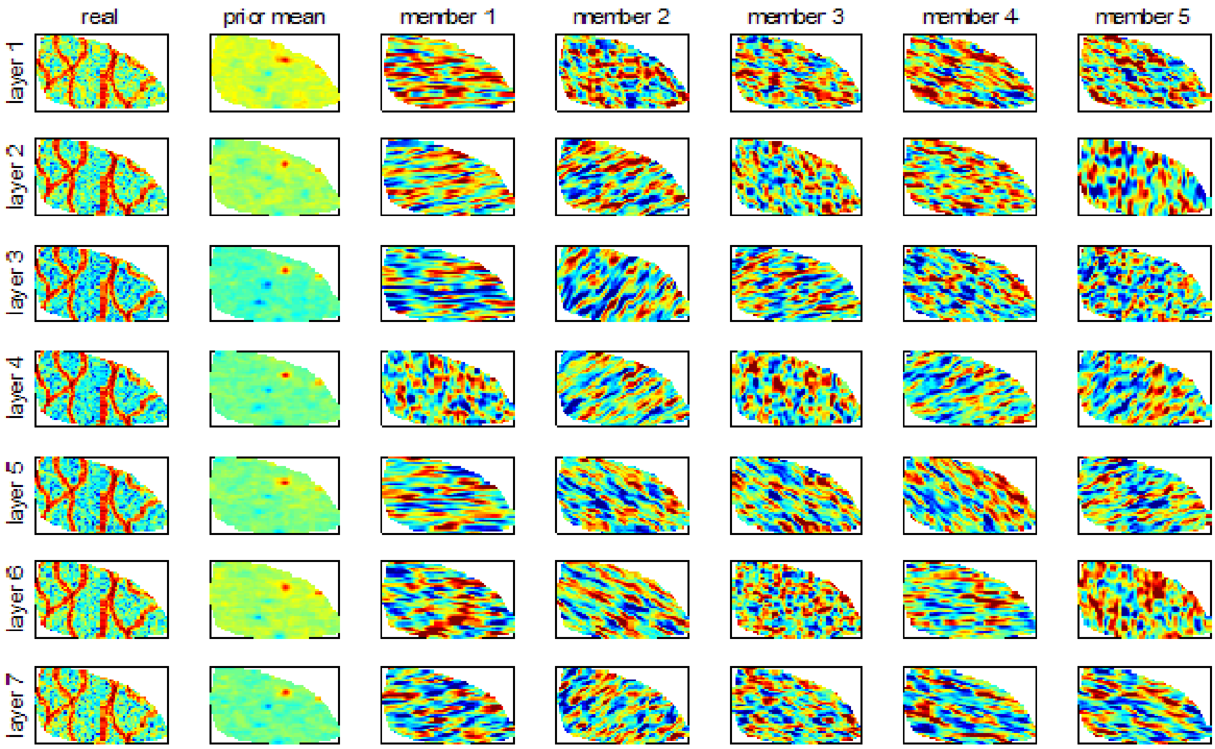

Fig. 4: Permeability fields per layer. First column: true values. Second column: prior ensemble average. Third to seventh column: randomly chosen prior ensemble members.

We used Corey-type relative permeabilities and zero capillary pressures. The relevant rock and fluid properties have been displayed in **Table 1**. The reservoir model, which was first used in Van Essen et al (2006), has no-flow boundaries at all sides and is produced through water flooding with 8 injectors and 4 producers. The injectors and producers are perforated in all seven layers. We used a proprietary large-scale reservoir simulator equipped with adjoint functionality to perform flooding optimization under well rate and bottom-hole pressure constraints (Kraaijevanger et al., 2007), and an in-house Matlab-based implementation of the ensemble Kalman filter to perform data assimilation. The initial ensemble of reservoir models was created with in-house geostatistical software. The second column of Fig. 4 displays the ensemble average for each layer and the third to seventh column display five of the 100 realizations. We created Gaussian random fields for permeability in each layer, conditioned to the well bore data, and with a randomly-oriented ellipsoidal covariance with a randomly-chosen correlation length between 4 and 8 grid blocks.

Economic data

We used an oil price of 283 $\$/m^3$, water production costs of 31.5 $\$/m^3$, water injection costs of 0 $\$/m^3$ and a discount rate of 15%. A simple NPV as defined in equation (9) was used as optimization objective. During updates of the control strategy, the discounting was always performed starting from the update time as would be done in a real situation where decisions are based on ‘forward-looking economics’. However, in order to compare the results of the different strategies we express all results in terms of NPV discounted with respect to the start of production. The total producing life of the reservoir was taken as 8 years (2922 days) and optimization was performed with respect to this fixed end time.

Control strategies

We performed six experiments using a reactive control strategy, in the remainder referred to as the ‘reactive case’, an open-loop control strategy, referred to as the ‘ideal case’, and four closed-loop control strategies. The closed-loop strategies used four different optimization frequencies increasing from once per 4 years to once per 2 years, then once per year and finally once per 30 days. For all experiments the injectors were operated on maximum rate constraints of 48 m^3/d and maximum pressure constraints of 41.4 MPa which is 1.4 MPa above the initial reservoir pressure (at top perforations). The producers were operated on minimum bottom hole pressure constraints of 38.3 MPa which is 1.7 MPa below the initial reservoir pressure and maximum total liquid rate constraints of 318 m^3/d.

Table 1 – Geological and fluid properties of the virtual asset.

Symbol	*Variable*	*Value*	*Units*
ϕ	Porosity	0.2	-
c_o	Rock compressibility	1.0×10^{-10}	1/Pa
c_w	Water compressibility	1.0×10^{-10}	1/Pa
c_r	Rock compressibility	0	1/Pa
ρ_o	Oil density (@1 bar)	900	kg/m^3
ρ_w	Water density (@1 bar)	1000	kg/m^3
μ_o	Oil dynamic viscosity	1.0×10^{-3}	Pa s
μ_w	Water dynamic viscosity	1.0×10^{-3}	Pa s
k_{ro}^0	Endpoint relative permeability, oil	0.8	-
k_{rw}^0	Endpoint relative permeability, water	0.6	-
n_o	Corey exponent, oil	4	-
n_w	Corey exponent, water	3	-
S_{or}	Residual oil saturation	0.15	-
S_{wc}	Connate water saturation	0.20	-
p_{init}	Initial reservoir pressure @ top perfs.	40	MPa

During the reactive case scenario the pressure constraints in the injectors and the rate constraints in the producers were never reached. Shut-in of the producers occurred at 90% water cut which corresponds to the economic limit for production under the given oil price and water costs. For the ideal case we performed open-loop optimization of the injector rates and producer pressures directly on the virtual asset under the constraints specified above. During closed-loop control, the injectors were operated by prescribing their rates and the producers by prescribing their bottom hole pressures but also within the specified constraints. Because in the reactive case the injectors and producers always operated on their maximum rate and minimum pressure constraints respectively, in the closed-loop cases the injection and production rates were effectively allowed to be reduced compared to the reactive case but not to be increased. During four different closed-loop experiments, the well controls were allowed to change at different frequencies. The highest frequency was once per 30 days, and with a total producing life of 2922 days and 12 wells this resulted in an optimization problem with 1164 input variables (control variables). Closed-loop optimization was performed on the mean of the updated ensemble using a steepest ascent algorithm with adjoint-derived gradient information.

Data assimilation

Synthetic production data were generated using forward simulation of the virtual asset, either using the reactive strategy to generate the initial data, or using prescribed rates (in the injectors) or bottom pressures (in the producers) while operating in open-loop or closed-loop mode. This resulted in synthetic bottom hole pressure and phase rate measurements for all wells at 30-day intervals. We used a standard ensemble Kalman filter implementation to update the natural log of the permeability, the pressures and the saturation values in all active grid blocks. Saturations were forced to stay within the moveable range through resetting values exceeding this range to residual saturations. Permeabilities were forced to stay within the range 50 – 20,000 mDa. All ensemble members were simulated by prescribing total liquid rates, i.e. without pressure constraints, as provided by the synthetic production data, resulting in pressures and phase rates as predicted output. We used standard deviations for the oil rates, water rates and pressures of 15 m^3/d, 15 m^3/d and 2.8 MPa respectively. We did not iterate the assimilation and did not apply any localization.

Results

Fig. 5 displays the NPV for each of the six experiments, and the discounted contributions from water and oil production. In terms of NPV the ideal case has the highest value and the reactive case the lowest with the closed-loop results gradually increasing with increasing optimization frequency. There is not much difference between the discounted oil revenues for the ideal case and for the closed-loop cases, although they are all clearly higher than for the reactive case. However, the discounted water costs display a clear reduction with increasing optimization frequency, except for a seemingly anomalous result for the once-per-two-year case. The NPV is monotonously increasing with increasing optimization frequency, also for the once-per-two year case because for that case not only the water production is lower, but also the oil production. The NPV values for the closed-loop cases are 6.68, 8.29, 8.30 and 8.71 % higher than for the reactive case, while the NPV for the once-per-30-days case is only 0.15% lower than the NPV for the ideal case (which is 8.86 % higher than the reactive case). **Fig. 6**

displays the results of the six experiments in terms of produced oil and water rates. The reactive strategy (purple lines) is clearly the worst performing one. Using a closed-loop strategy with an increasing optimization frequency results in a reduction in water production, in line with the data in Fig. 5. The once-per-two-year results (blue dashed line) deviate from the trend after 1700 days and even correspond to a lower water production than in the ideal case (black dashed line). The effect of increasing the optimization frequency seems to have little influence on the oil production and all closed-loop results (red lines) are close to the result for the ideal case (black solid line, hardly visible), which is considerably better than the one for the reactive case (purple solid line).

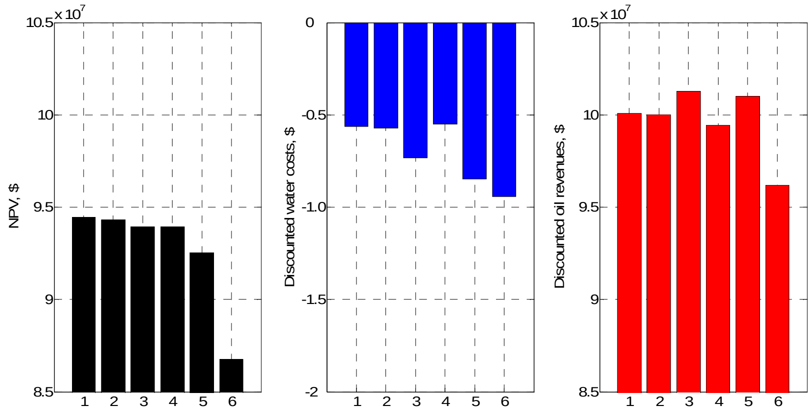

Fig. 5: NPV (black) and contributions to NPV from water production (blue) and oil production (red) for six experiments: 1) ideal case; 2) 30 days case; 3) one-year case; 4) two-year case; 5) four-year case; 6) reactive base case.

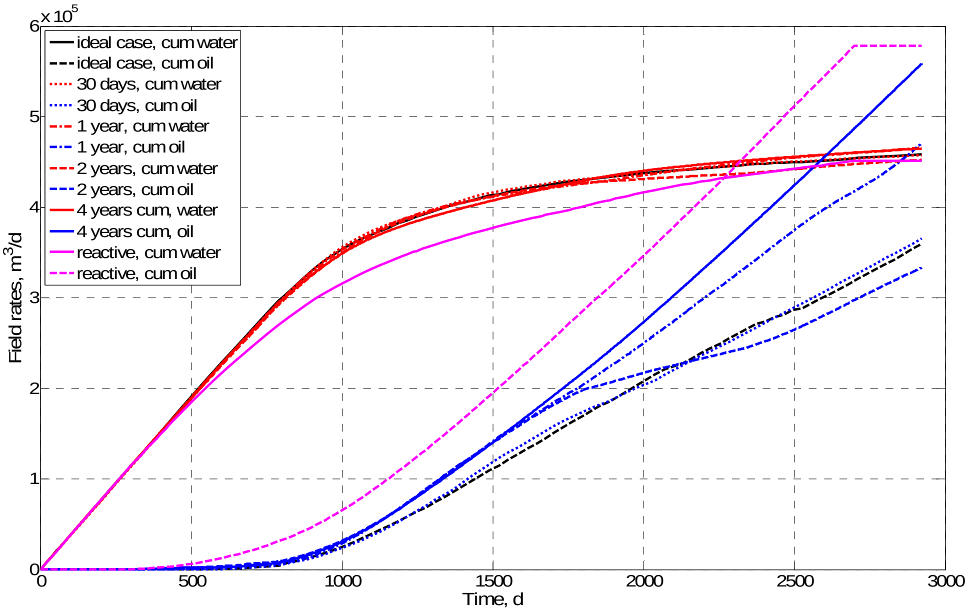

Fig. 6: Results for the six experiments: cumulative oil rates and produced water rates.

Discussion

Fig. 7 displays the updated ensemble averages at different moments in time for the once-per-30-days closed-loop case, displaying a gradual increase in reservoir heterogeneity which, however, never reaches the exact pattern of the truth case as displayed in the left column. **Fig. 8** shows the fourth layer of the true reservoir and the corresponding ensemble average for the once-per-30-days case after eight years, i.e. at the end of the producing life of the reservoir, and also these two permeability fields are significantly different. However, as illustrated in Figs. 5 and 6, the simulated reservoir performance for these two cases is nearly identical. It is well known that history matching is an ill-posed problem, i.e. it allows many solutions (permeability fields in our case) that reproduce the same historic production data; see e.g. Oliver et al. (2008). This example illustrates that such ill-posedness is not necessarily always problematic. In particular if we attempt to optimize the flooding performance of a reservoir by manipulating pressures and flow rates in a fixed well configuration there is only a limited amount of control that we can exercise on the reservoir states (i.e. pressures and saturations). Especially pressures that are some distance away from the wells and saturations away from the oil-water front are generally poorly controllable. At the same time, the amount of information that we can infer from production data is also limited. This concerns in particular the observability of state variables and the identifiability of parameters at some distance from the wells. For a situation where we estimate reservoir properties with the aid of production data from the same wells that we use to control the reservoir flooding, the limited amount of information that can be obtained from the well data may just be enough to optimize the flooding performance within the limited room that is available for well control. A formal analysis of the concepts of observability, controllability and identifiability as applied to single-phase reservoir flow was recently published by Zandvliet et al. (2008). Work to extend these concepts to two-phase flow is ongoing. We like to stress that we acknowledge that for realistic reservoir management geological knowledge is essential, in particular when there is room to plan for new wells. However, we also like to stress that the essential information in a reservoir model for a particular well configuration can often be represented with a much less complex representation than suggested by the large number of grid blocks in typical reservoir models. This implies that there is room for reparameterization of the permeability field to reduce the number of model parameters, and for low-order modeling using system-theoretical concepts to reduce the number of model states. For references to techniques for parameter and model-order reduction we refer to the end of the Appendix.

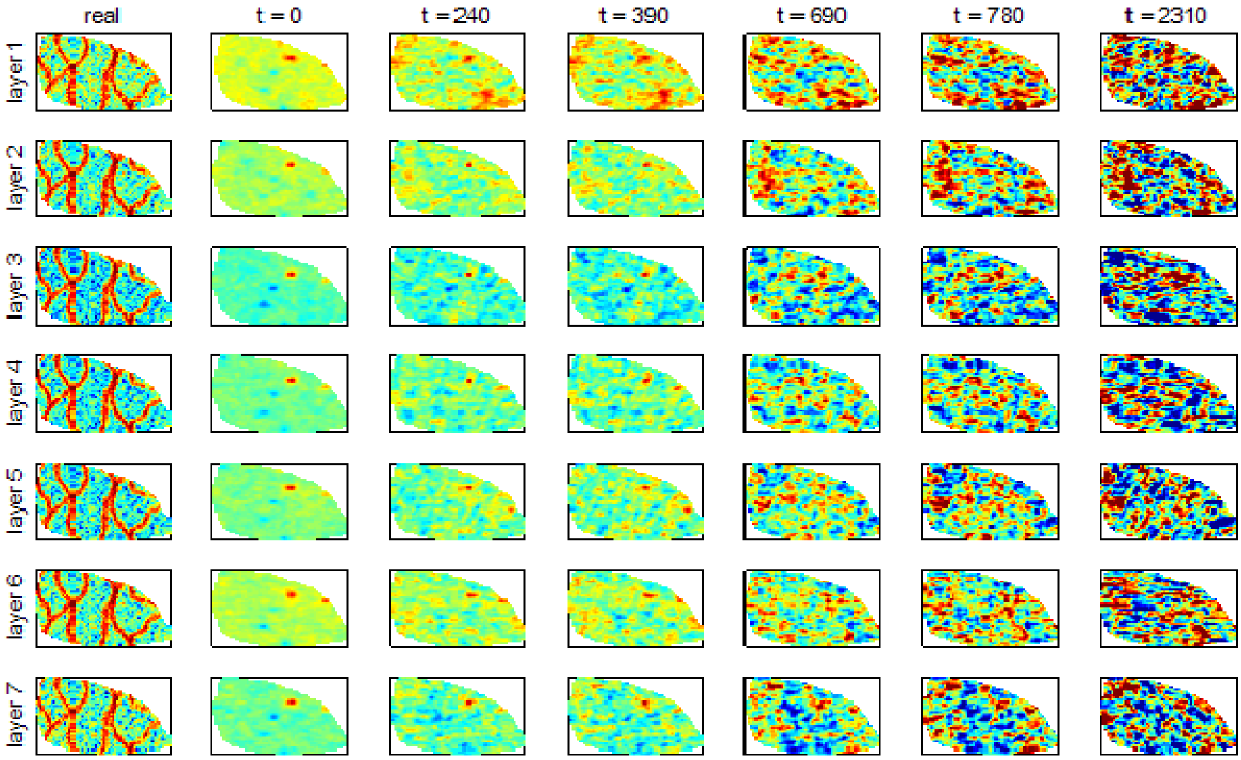

Fig. 7: Permeability fields per layer. First and second column: true values and prior ensemble averages (equal to first two columns of Fig. 4). Third to seventh column: ensemble averages at different moments in time for the once-per-30-days closed-loop case.

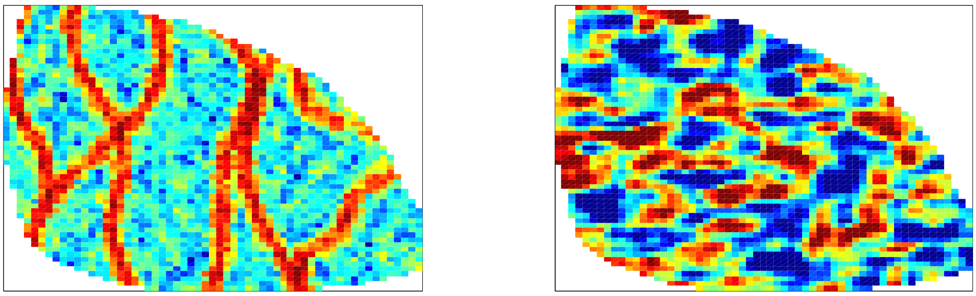

Fig. 8: Permeability fields for layer 4. Left: true reservoir. Right: ensemble average after 2922 days (final time) for the once-per-30-days closed-loop case.

Fig. 9 displays the well rates for the ideal case and the reactive case. It can be seen that the general effect of the optimization algorithm is to shut in the injection wells earlier than for the reactive case and to prescribe bottom hole pressures in the producers that cause much more irregular rates. In practice such irregular rates will not be acceptable. In fact it is doubtful if a prescribed production strategy based on reservoir simulation models will ever be acceptable for production engineering purposes. In particular, it is very unlikely that a producer will be shut for long-term reservoir management purposes when it produces at high rate. Manipulation of the injectors will probably be less of a problem. A practical solution to implement optimized well rates or pressures will probably require an envelope of maximum and minimum allowable rates and pressures defined on the basis of reservoir simulation, leaving sufficient space for the production engineer to operate the wells using short-term considerations. Probably some form of hierarchical optimization will be required as is customary in the process industry; see e.g. Saputelli et al. (2005, 2006) for further details. Fortunately there appears to be room to for maneuvering, because we frequently encountered situations where considerably different inputs resulted in identical NPV values. In fact the seemingly anomalous result for the once-every-two years closed-loop case is probably also an illustration of this effect. Another example is given by **Fig. 10** which displays the injection rate in well 5 for the once-per-30-days case. Initially we performed the optimization with the 'nervous' optimal strategy as indicated with the dotted line. However, we repeated the simulation with smoothed optimal rates and pressures, using Fourier-based filtering to remove the high-frequency components; and obtained identical results for the NPV. This illustrates that, just as was the case for the data assimilation problem, the flooding optimization problem is ill-posed and contains many more control variables than necessary. Therefore, just as in data assimilation, there is scope for reparameterization, see e.g. Lien et al. (2008), and, more importantly, for optimization of long-term reservoir performance while maintaining freedom to perform short-term production optimization.

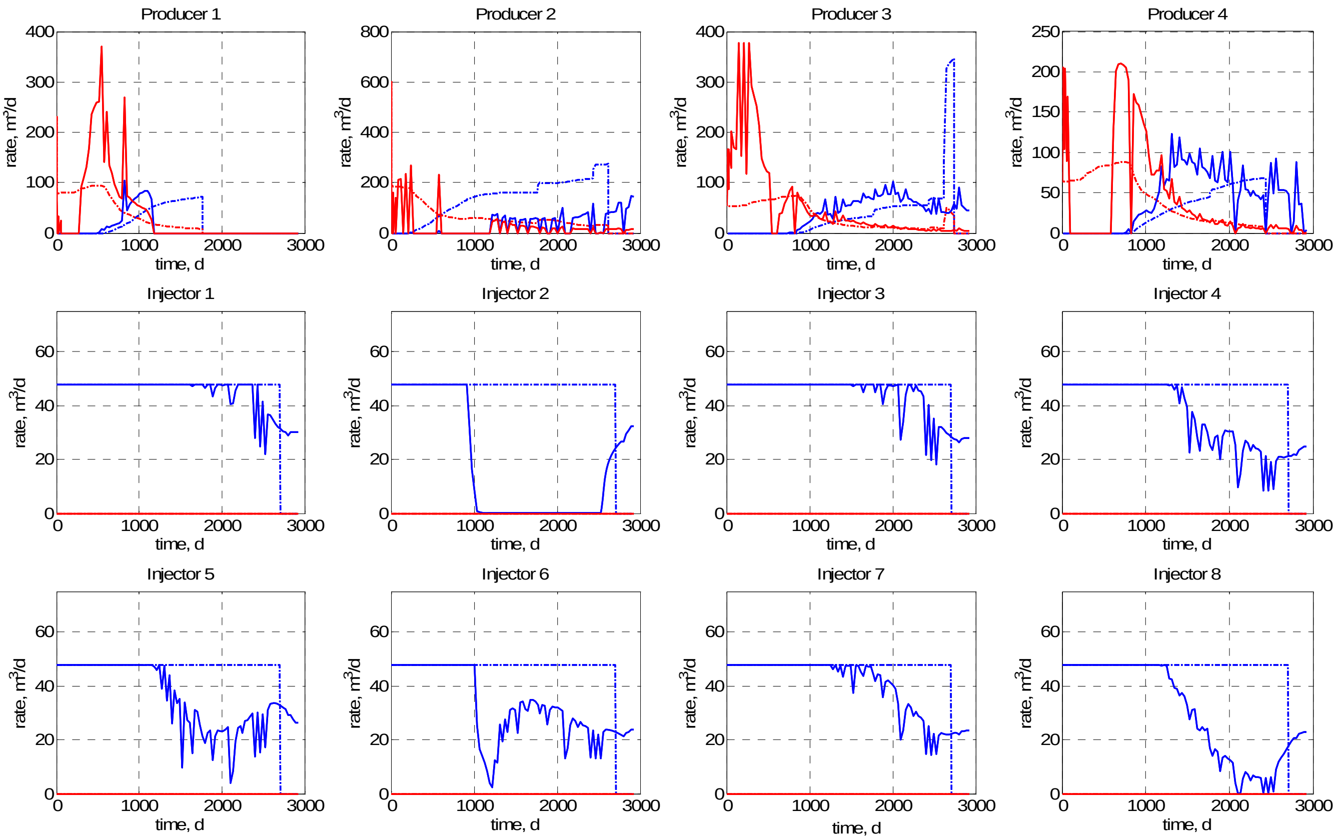

Fig. 9: Well rates for the ideal case (solid lines) and the reactive case (dash-dotted lines); red:oil; blue: water.

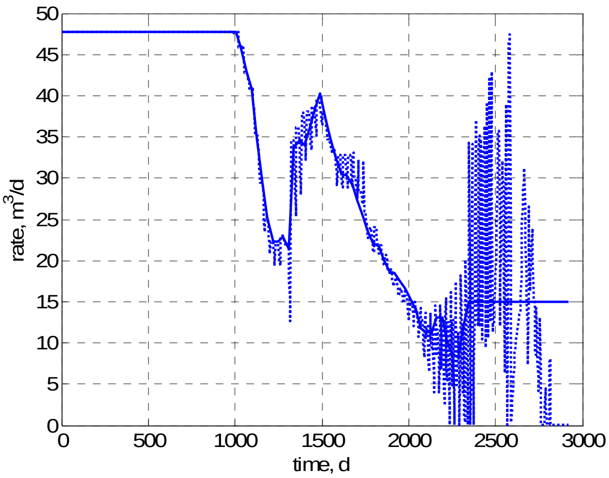

Fig. 10: Injection rate in well 5 for the once-per-30-days case. Dotted line: initial 'nervous' optimal rate. Solid line: smoothed rate.

Conclusions

We performed a numerical experiment to verify the hypothesis that "It will be possible to significantly increase life-cycle value by changing reservoir management from a 'batch-type' to a 'near-continuous' model-based controlled activity." Although we only performed a single experiment, which therefore does not bear any statistical significance, we conclude that for this example increasing the optimization frequency indeed resulted in an increase in NPV. Specifically we found that the NPV values for the closed-loop cases were 6.68, 8.29, 8.30 and 8.71 % higher than for the reactive case, while the NPV for the once-per-30-days case was only 0.15% lower than the NPV for the ideal, open-loop case (which is 8.86 % higher than the reactive case).

We illustrated that for closed-loop reservoir management with a fixed well configuration, the use of considerably different reservoir models may lead to near-identical results in terms of NPV. This implies that in such cases the essential information may be represented with a much less complex model than suggested by the large number of grid blocks in typical reservoir models. This also implies that there is room for reparameterization of the permeability field to reduce the number of model parameters, and for low-order modeling using system-theoretical concepts to reduce the number of model states.

We also illustrated that the optimal rates and pressures as obtained by open- or closed-loop optimization are often too irregular to be practically applicable. A practical solution will probably require an envelope of allowable rates and pressures defined on the basis of reservoir simulation, leaving sufficient space for the production engineer to operate the wells using short-term considerations. Fortunately, just as was the case for the data assimilation problem, the flooding optimization problem usually contains many more control variables than necessary, allowing for optimization of long-term reservoir performance while maintaining freedom to perform short-term production optimization.

Acknowledgments

The contents of this paper reflect the research of many people at Delft University of Technology (DUT), Shell International Exploration and Production (SIEP) and the Dutch organization for applied scientific research TNO. Several PhD and MSc students at DUT contributed to this work over the past years, and we like to thank one of them, Gijs van Essen, in particular for his assistance with the example used in this paper. Financial support for the research at DUT is provided by the following consortia and sponsors: ISAPP (TNO and Shell), VALUE (Shell and Senter/Novem) and DELPHI (multiple sponsors).

References

Aitokhuehi, I, and Durlofsky, L.J. 2005. Optimizing the performance of smart wells in complex reservoirs using continuously updated geological models. *Journal of Petroleum Science and Engineering* **48** (3 & 4): 254-264. DOI: 10.1016/j.petrol.2005.06.004.

Alhuthali, A.H., Oyerinde, D. and Datta-Gupta, A. 2007. Optimal water flood management using rate control. *SPEREE* **10** (5): 539-551. DOI: 10.2118/102478-PA.

Alhuthali, A.H., Datta-Gupta, A., Yuen, B. and Fontanilla, J.P. 2008. Optimal rate control under geologic uncertainty. Paper SPE 113628 presented at the SPE/DOE Symposium on Improved Oil Recovery. DOI: 10.2118/113628-MS.

Alpak, F.O., van Kats, F. and Hohl, D. 2009. Stochastic history matching of a deepwater turbidite reservoir. Paper SPE 119030 presented at the SPE Reservoir Simulation Symposium, The Woodlands, USA, 2–4 February.

Asheim, H.. 1988. Maximization of water sweep efficiency by controlling production and injection rates. Paper SPE 18365 presented at the SPE European Petroleum Conference, London, UK, October 16-18. DOI: 10.2118/18365-MS.

Baird, J. and Dawson, C. 2007. The representer method for two-phase flow in porous media. *Computational Geosciences* **11** (3): 235-248. DOI: 10.1007/s10596-007-9048-8.

Barker, J.W., Cuypers, M. and Holden, L. 2001. Quantifying uncertainty in production forecasts: Another look at the PUNQ-S3 problem. *SPEJ* **6** (4) 433-441. DOI: 10.2118/74707-PA.

Bennett, A.F. 2002. *Inverse modeling of the ocean and the atmosphere*. Cambridge University Press, Cambridge.

Brouwer, D.R. and Jansen, J.D. 2004. Dynamic optimization of water flooding with smart wells using optimal control theory. *SPEJ* **9** (4): 391-402. DOI: 10.2118/78278-PA.

Brouwer, D.R., Naevdal, G., Jansen, J.D., Vefring, E. and van Kruijsdijk, C.P.J.W. 2004. Improved reservoir management through optimal control and continuous model updating. Paper SPE 90149 presented at the SPE Annual Technical Conference and Exhibition, Houston, Texas, USA, 26-29 September. DOI: 10.2118/90149-MS.

Caers, J. 2003. History matching under training-image-based geological model constraints. *SPEJ* **8** (3): 218-226. DOI: 10.2118/74716-PA.

Cardoso, M.A., Durlofsky, L.J. and Sarma, P. 2008. Development and application of reduced-order modeling procedures for subsurface flow simulation. *Int. J. for Numerical Methods in Engineering*. Published on-line. DOI: 10.1002/nme.2453.

Chavent, G., Dupuy, M. and Lemonnier, P. 1975. History matching by use of optimal theory. *SPEJ* **15** (1): 74-86. DOI: 10.2118/4627-PA.

Chen, Y., Oliver, D.S. and Zhang, D. 2008. Efficient ensemble-based closed-loop production optimization. Paper SPE 112873 presented at the SPE/DOE Improved Oil Recovery Symposium, Tulsa, USA, 19-23 April, DOI: 10.2118/112873-MS.

Chen, Y., Oliver and D.S. 2009. Application of ensemble-based closed-loop production optimization on Brugge field. Paper SPE 118962 presented at the SPE Reservoir Simulation Symposium, The Woodlands, USA, 2–4 February.

Chierici, G.L.. 1992. Economically improving oil recovery by advanced reservoir management. *Journal of Petroleum Science and Engineering* **8** (3): 205-219. DOI: 10.1016/0920-4105(92)90034-X.

De Montleau, P., Cominelli, A., Neylon, K., Rowan, D., Pallister, I., Tesaker, O. and Nygard, I. 2006. Production optimization under constraints using adjoint gradients. *Proc. 10th European Conference on the Mathematics of Oil Recovery (ECMOR X)*, Paper A041, Amsterdam, The Netherlands, September 4-7.

Devegowda, D., Arroyo-Negrete, E., Datta-Gupta, A. and Douma, S.G. 2007. Efficient and robust reservoir model updating using ensemble Kalman filter with sensitivity-based covariance localization. Paper SPE 106144, presented at the SPE Reservoir Simulation Symposium, Houston, USA, 26-28 February. DOI: 10.2118/106144-MS.

Erbaş, D. and Christie, M.A. 2007. Effect of sampling strategies on prediction uncertainty estimation. Paper SPE 106229, presented at the SPE Reservoir Simulation Symposium, Houston, USA, 26-28 February. DOI: 10.2118/106229-MS.

Evensen, G. 1994. Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics. *J. Geophys. Res.* **99** (C5): 10143-10162.

Evensen, G. 2007. *Data assimilation – The Ensemble Kalman Filter*. Springer, Berlin.

Gavalas, G.R., Shah, P.C. and Seinfeld, J.H. 1976. Reservoir history matching by Bayesian estimation. *SPEJ* **16** (6): 337-350. DOI: 10.2118/5740-PA.

Gildin, E., Klie, H., Rodriguez, A., Wheeler, M.F. and Bishop, R.H. 2006. Development of low-order controllers for high-order reservoir models and smart wells. Paper SPE 102214 presented at the SPE Annual Technical Conference and Exhibition, San Antonio, USA, 24-27 September. DOI: 10.2118/102214-MS.

Gu, Y. and Oliver, D. 2007. An iterative ensemble Kalman filter for multiphase fluid flow data assimilation. *SPEJ* **12** (4): 438-446. DOI: 10.2118/108438-PA.

Heijn, T., Markovinović, R. and Jansen, J.D. 2004. Generation of low-order reservoir models using system-theoretical concepts. *SPEJ* **9** (2): 202-218. DOI: 10.2118/88361-PA.

Jafarpour, B. and McLaughlin, D. 2007. Efficient permeability parameterization with the discrete cosine transform. Paper SPE 106453 presented at the SPE Reservoir Simulation Symposium, Houston, USA, 26-28 February. DOI: 10.2118/106453-MS.

Jansen, J.D., Brouwer, D.R., Naevdal, G. and van Kruijsdijk, C.P.J.W. 2005. Closed-loop reservoir management. *First Break* **23**: 43-48.

Jansen, J.D., Durlofsky, L., Aziz, K. and van Kruijsdijk, C.P.J.W. 2006. Editorial for special issue on "Closed-loop reservoir management". *Computational Geosciences* **10** (1): 1-2. DOI: 10.1007/s10596-005-9015-1. For a listing of papers see: http://www.springerlink.com/content/rnvrk3737207/?p=a70453a2ddf145988e456abf054da91b&pi=10 .

Jansen, J.D., Bosgra, O.H. and Van den Hof, P.M.J. 2008. Model-based control of multiphase flow in subsurface oil reservoirs. *Journal of Process Control* **18**: 846-855. DOI: 10.1016/j.jprocont.2008.06.011.

Kraaijevanger, J.F.B.M., Egberts, P.J.P., Valstar, J.R. and Buurman, H.W. 2007. Optimal water flood design using the adjoint method. Paper SPE 105764 presented at the SPE Reservoir Simulation Symposium, Houston, USA, 26-28 February. DOI: 10.2118/105764-MS.

Li, R., Reynolds, A.C., and Oliver, D.S. 2003. History matching of three-phase flow production data. *SPEJ* **8** (4): 328-340. DOI: 10.2118/87336-PA.

Lien, M., Brouwer, D.R., Manseth, T. and Jansen, J.D. 2008. Multiscale regularization of flooding optimization for smart field management. *SPEJ* **13** (2): 195-204. DOI: 10.2118/99728-PA.

Lorentzen, R.J., Berg, A.M., Naevdal, G. and Vefring, E.H. 2006. A new approach for dynamic optimization of water flooding problems. Paper SPE 99690 presented at the SPE Intelligent Energy Conference and Exhibition, Amsterdam, The Netherlands, 25-27 February. DOI: 10.2118/99690-MS.

Lorentzen, R.J., Shafieirad, A. and Naevdal, G. 2009. Closed-loop reservoir management using the ensemble Kalman filter and sequential quadratic programming. Paper SPE 119101 presented at the SPE Reservoir Simulation Symposium, The Woodlands, USA, 2–4 February.

Markovinović, R. and Jansen, J.D. 2006. Accelerating iterative solution methods using reduced-order models as solution predictors. *Int. J. for Numerical Methods in Engineering* **68** (5) 525-541, DOI: 10.1002/nme.1721.

Naevdal, G., Johnsen, L.M., Aanonsen, S.I., Vefring, E.H. 2005. Reservoir monitoring and continuous model updating using ensemble Kalman filter. *SPEJ* **10** (1): 66-74. DOI: 10.2118/84372-PA.

Naevdal, G., Brouwer, D.R. and Jansen, J.D. 2006. Water flooding using closed-loop control. *Computational Geosciences* **10** (1): 37-60. DOI: 10.1007/s10596-005-9010-6.

Oliver, D.S., Reynolds, A.C. and Liu, N. 2008. *Inverse theory for petroleum reservoir characterization and history matching*. Cambridge University Press, Cambridge.

Omre, H. and Lødøen, O.P. 2004. Improved production forecasts and history matching using approximate fluid-flow simulators. *SPEJ* **9** (3): 339-351. DOI: 10.2118/74691-PA.

Overbeek, K.M., Brouwer, D.R., Nævdal, G. and van Kruijsdijk, C.P.J.W. 2004. Closed-loop water flooding. *Proc. 9th European Conference on the Mathematics of Oil Recovery (ECMOR IX)*, Cannes, France, August 28 – September 2.

Peters, E., Arts, R.J., Brouwer, G.K., Geel, C. 2009. Results of the Brugge benchmark study for flooding optimization and history matching. Paper SPE 119094 presented at the SPE Reservoir Simulation Symposium, The Woodlands, USA, 2–4 February.

Przybysz-Jarnut, J.K., Hanea, R.G., Jansen, J.D. and Heemink, A.W. 2007. Application of the representer method for parameter estimation in numerical reservoir models. *Computational Geosciences* **11** (1): 73-85, DOI: 10.1007/s10596-006-9035-5.

Ramirez, W.F.. 1987. *Application of optimal control theory to enhanced oil recovery.* Elsevier, Amsterdam.

Reynolds, A.C. and Zafari, M. 2006. Iterative forms of the ensemble Kalman filter. *Proc. 10th European Conference on the Mathematics of Oil Recovery (ECMOR X)*. Paper A030, Amsterdam, The Netherlands, 4 - 7 September.

Rodrigues, J.R.P. 2006. Calculating derivatives for automatic history matching. *Computational Geosciences* **10** (1): 119-136. DOI: 10.1007/s10596-005-9013-3.

Roggero, F. and Hu, L.Y. 1998. Gradual deformation of continuous geostatistical models for history matching. Paper SPE 49004 presented at the SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, USA, 27-30 Sept. DOI: 10.2118/49004-MS.

Rommelse, J.R., Jansen, J.D. and Heemink, A.W. 2007. An efficient gradient-based parameter estimation algorithm using representer expansions. Submitted for publication. Preprint available as *Report 07-05 of the Dept. of Mathematical Analysis*, Delft University of Technology, Delft, The Netherlands.

Sahni, I. and Horne, R.N. 2005. Multiresolution wavelet analysis for improved reservoir description. *SPEREE* **8** (1): 53-69 DOI: 10.2118/87820-PA.

Saputelli, L., Nikolaou, M. and Economides, M.J. 2005. Self-learning reservoir management. *SPEREE* **8** (6): 534-547. DOI: 10.2118/84064-PA.

Saputelli, L., Nikolaou, M. and Economides, M.J. 2006. Real-time reservoir management: a multi-scale adaptive optimization and control approach. *Computational Geosciences* **10** (1) 61-96. DOI: 10.1007/s10596-005-9011-5.

Sarma, P., Aziz, K. and Durlofsky, L.J. 2005a. Implementation of adjoint solution for optimal control of smart wells. Paper SPE 92864 presented at the SPE Reservoir Simulation Symposium, Houston, USA, 31 January – 2 February. DOI: 10.2118/92864-MS.

Sarma, P., Durlofsky, L.J. and Aziz, K. 2005b. Efficient closed-loop production optimization under uncertainty. Paper SPE 94241 presented at the SPE Europec/EAGE Annual Conference, Madrid, Spain, 13-16 June. DOI: 10.2118/94241-MS.

Sarma, P., Durlofsky, L.J., Aziz, K. and Chen, W.H.. 2006a. Efficient real-time reservoir management using adjoint-based optimal control and model updating. *Computational Geosciences* **10** (1): 3-36. DOI: 10.1007/s10596-005-9009-z.

Sarma, P., Durlofsky, L.J., Aziz, K. and Chen, W.H. 2007. A new approach to automatic history matching using kernel PCA. Paper 106176 presented at the SPE Reservoir Simulation Symposium, Houston, Texas, USA, 26-28 February. DOI: 10.2118/106176-MS.

Sarma, P., Chen, W.H. Durlofsky, L.J. and Aziz, K. 2008. Production optimization with adjoint models under nonlinear control-state path inequality constraints, *SPEREE* **11** (2): 326-339. DOI: 10.2118/99959-PA.

Sarma, P., Durlofsky, L.J. and Aziz, K.. 2008. Computational techniques for closed-loop reservoir modeling with application to a realistic reservoir. *Petroleum Science and Technology* **26** (10 & 11): 1120-1140. DOI: 10.1080/10916460701829580.

Schulze-Riegert, R.W., Axmann, J.K., Haase, O., Rian, D.T., You, Y.-L. 2002. Evolutionary algorithms applied to history matching of complex reservoirs. *SPEREE* **5** (2): 163-173. DOI: 10.2118/77301-PA.

Skjervheim, J.A., Evensen, G., Aanonsen, S.I., Ruud, B.O. and Johansen, T.A. 2007. Incorporating 4D seismic data in reservoir simulation models using ensemble Kalman filter. *SPEJ* **12** (3): 282-292. DOI: 10.2118/95789-PA.

Sudaryanto, B., and Yortsos, Y.C. 2000. Optimization of fluid front dynamics in porous media using rate control. *Physics of Fluids* **12** (7): 1656-1670.

Tarantola, A. 2005. *Inverse problem theory and methods for model parameter estimation*. SIAM, Philadelphia.

Thiele, M.R. and Batycky, R.P. 2006. Using streamline-derived injection efficiencies for improved water flood management. *SPEREE* **9**: 187-196. DOI: 10.2118/84080-PA.

Vakili-Ghahani, A. and Jansen, J.D. 2008. Control relevant upscaling. Paper SPE 113647 presented at the 2008 SPE Europec/EAGE Annual Conference and Exhibition, Rome, Italy, 9–12 June. DOI: 10.2118/113647-MS.

Van Doren, J.F.M., Markovinović, R. and Jansen, J.D. 2006. Reduced-order optimal control of water flooding using POD. *Computational Geosciences* **10** (1) 137-158. DOI: 10.1007/s10596-005-9014-2.

Van Essen, G.M., Zandvliet, M.J., Van den Hof, P.M.J., Bosgra, O.H. and Jansen, J.D. 2006. Robust water flooding optimization of multiple geological scenarios. Paper SPE 102913 presented at the SPE Annual Technical Conference and Exhibition, San Antonio, USA, 24-27 September. DOI: 10.2118/102913-MS.

Vasco, D.W., Soon, S. and Datta-Gupta, A. 1999. Integrating dynamic data into high-resolution reservoir models using streamline-based analytical sensitivity coefficients. *SPEJ* **4** (4) 389-399. DOI: 10.2118/59253-PA.

Virnovski, G.A. 1991. Water flooding strategy design using optimal control theory. *Proc. 6th European Symp. on IOR*, Stavanger, Norway, 437-446.

Wang, C., Li, G. and Reynolds, A.C. 2007. Production optimization in closed-loop reservoir management. Paper SPE 109805 presented at the SPE Annual Technical Conference and Exhibition, Anaheim, USA, 11-14 November. DOI: 10.2118/109805-MS.

Wen, X.-H. and Chen. W.H. 2006. Real-time reservoir model updating using Ensemble Kalman filter with confirming option. *SPEJ* **11** (4): 431-442. DOI: 10.2118/92991-PA.

Yang, D., Zhang, Q., Gua, Y. 2003. Integrated optimization and control of the production-injection operation systems for hydrocarbon reservoirs. *Journal of Petroleum Science and Engineering* **37** (1 & 2): 69-81. DOI: 10.1016/S0920-4105(02)00311-X.

Yang, C., Nghiem L., Card, C. and Bremeir, M. 2007. Reservoir model uncertainty quantification through computer-assisted history matching. Paper SPE 109825 presented at the SPE Annual Technical Conference and Exhibition, Anaheim, USA, 11-14 November. DOI: 10.2118/109825-MS.

Yeten, B., Brouwer, D.R., Durlofsky, L.J. and Aziz, K. 2004. Decision analysis under uncertainty for smart well deployment. *Journal of Petroleum Science and Engineering* **43** (3 & 4): 183-199. DOI: 10.1016/j.petrol.2004.02.013.

Zafari, M. and Reynolds A.C. 2007. Assessing the uncertainty in reservoir description and performance predictions with the ensemble Kalman filter. *SPEJ* **12** (3): 382-391. DOI: 10.2118/95750-PA.

Zakirov, I.S., Aanonsen, S.I., Zakirov, E.S., and Palatnik, B.M. 1996. Optimization of reservoir performance by automatic allocation of well rates. *Proc. 5th European Conference on the Mathematics of Oil Recovery (ECMOR V)*, Leoben, Austria.

Zandvliet, M.J., Bosgra, O.H., Jansen, J.D., Van den Hof, P.M.J. and Kraaijevanger, J.F.B.M.. 2007. Bang-bang control and singular arcs in reservoir flooding. *Journal of Petroleum Science and Engineering* **58** (1 & 2): 186-200. DOI: 10.1016/j.petrol.2006.12.008.

Zandvliet, M.J., van Doren, J.F.M., Bosgra, O.H., Jansen, J.D. and van den Hof, P.M.J. 2008. Controllability, observability and identifiability in single-phase porous media flow. Published online in *Computational Geosciences*. DOI: 10.1007/s10596-008-9100-3.

Zhang, F., Skjervheim, J.A., Reynolds, A.C. and Oliver, D.S. 2005. Automatic history matching in a Bayesian framework, example applications. *SPEREE* **8** (3): 214-223. DOI: 10.2118/84461-PA.

Appendix: Flooding optimization and data assimilation techniques

Flooding optimization

Gradient-based and gradient-free techniques

Many numerical techniques are available to solve the flooding optimization problem defined in the body of the text. An important distinction is between methods that attempt to find the global optimum, and those that aim at finding a local optimum (which could be equal to the global optimum, but usually isn't). For realistic problems, all optimization techniques involve some form of iteration, and the 'local methods' will produce answers that are dependent on the initial guess used as starting point for the iteration. Another distinction is between gradient-based and gradient-free methods. Gradient-based methods make use of gradients ∇J_k, i.e. of column vectors of derivatives $\partial J / \partial u_{ik}$, to guide the iteration process. Here, u_{ik} represents a single element *i* of vector $\mathbf{u}_k$ at time *k*. Gradients of a function have the property that they point in the direction of maximum increase of the function value, which explains their significance to find the maximum (or the minimum) of a function. A disadvantage of gradient-based methods is that they usually converge to a local optimum, as opposed to some gradient-free techniques that can search for the global optimum. However, gradient-free methods require many more function evaluations (i.e. reservoir simulations) than gradient-based methods to find an optimum, which makes them unattractive for our purpose.

Obtaining gradients

The most straightforward way to obtain gradient information $\partial J / \partial u_{ik}$ is by repeating the forward reservoir simulation with a slightly perturbed input variable $\tilde{u}_{ik} = u_{ik} + \Delta u_{ik}$ resulting in a slightly perturbed objective function value $\tilde{J}$ such that we can use the approximation $\partial J / \partial u_{ik} \approx \Delta J / \Delta u_{ik} = (\tilde{J} - J)/(\tilde{u}_{ik} - u_{ik})$. However, to obtain the full gradient ∇J_k we need to repeat this perturbation for each input variable *i* at each time step *k*, which becomes computationally prohibitive for realistic flooding optimization problems. An approximate gradient vector can be obtained by perturbing all input variables simultaneously in a random fashion; see Wang et al. (2007). This so-called 'simultaneous perturbation stochastic approximation (SPSA)' method results in a sub-optimal gradient, but with significantly less computational effort than the full finite difference method. Another way to obtain an approximate gradient is to use the statistical relationship (cross-covariance) between the a number of randomly chosen control vectors and the corresponding objective function values, see Lorentzen et al. (2006), Wang et al. (2007) and Chen et al. (2008).

Adjoint-based techniques

In our work we have been using an alternative approach where the derivative information is obtained through the use of an adjoint equation; see Brouwer and Jansen (2004), Van Essen et al. (2006), Zandvliet et al. (2007) and Jansen et al. (2008). A major benefit of the adjoint method is that the gradient information is obtained using a single additional dynamic simulation, independent of the number of control variables. This gives it a computationally superior behavior compared to the finite difference, SPSA and ensemble methods. However, the price to pay is the need to program in the adjoint equations which is a major programming effort for any realistic reservoir simulation code. Adjoint-based techniques for flooding optimization were introduced in reservoir engineering for the optimization of tertiary recovery processes such as polymer or CO_2 flooding; see Ramirez (1987). The first paper on gradient-based control of water flooding is Asheim (1988), followed by, among others, Virnovsky (1991), Zakirov et al. (1996) and Sudaryanto and Yortsos (2000, 2001). However, industry uptake of these methods was almost absent until the advent of 'smart well' and 'smart fields' technology which caused a revival of interest; see Brouwer and Jansen (2004). Recently, a series of publications have appeared covering various aspects of adjoint-based optimization of reservoir flooding while several reservoir simulation packages have been equipped with the adjoint functionality. Implementation aspects have been addressed in Sarma et al. (2005a), computational issues in Zandvliet et al. (2007), regularization in Lien et al. (2008), and constraint handling in Sarma et al. (2005a, 2008), De Montleau et al. (2006) and Kraaijevanger et al. (2007).

Other techniques

If we disregard the water injection costs in objective function (6) and use a zero discount factor, the optimum is often reached when the water front reaches the production wells at the same moment in time. In particular when the wells are controlled on rates and if we can disregard compressibility effects, a very efficient way to perform the optimization is then with the aid of streamline-derived derivatives, see Alhuthali et al. (2007). We note that the results of such streamline-based life-cycle optimization may be different from instantaneous streamline-based optimization using 'pattern balancing' as described in e.g. Thiele and Batycky (2006). Further alternative methods to perform life-cycle flooding optimization use 'non-classical' methods such as genetic algorithms or simulated annealing; see e.g. Yang et al. (2003).

Robust optimization

One of the major challenges in reservoir engineering is taking decisions in the presence of very large uncertainties about the subsurface structure and the parameters that influence fluid flow. One of the ways to cope with this uncertainty during the field development phase of a reservoir is to use a set of different subsurface models, also known as an ensemble of geological realizations; see e.g. Yeten et al. (2004). It is then possible to use a robust ensemble-based optimization strategy to maximize a robust objective function J_{rob} which approximates the expected value of the objective function over all realizations according to

$$J_{rob}\left(\mathbf{u}_{1:K},\mathbf{y}_{1:K}^{1:N_R}\left(\mathbf{u}_{1:K}\right),\boldsymbol{\theta}^{1:N_R}\right)=\frac{1}{N_R}\sum_{i=1}^{N_R}J\left(\mathbf{u}_{1:K},\mathbf{y}_{1:K}^{i}\left(\mathbf{u}_{1:K}\right),\boldsymbol{\theta}^{i}\right), \tag{A.1}$$

where $\boldsymbol{\theta}^i$ and $\mathbf{y}^i$ are the parameter and output vectors of realizations $i = 1, \ldots, N_R$. Calculating the 'mean' gradients $(dJ_{rob}/d\mathbf{u}_k)^T$ of the robust objective function involves a linear operation in terms of the gradients of each realization, and can be done efficiently using an adjoint-based approach; see Sarma et al. (2005b) and van Essen et al. (2006). This approach has the advantage that the gradients of each realization can be calculated in a sequential manner instead of simultaneously, which would result in a considerable computational burden limiting the number of realizations that could be used. Calculating the gradients sequentially circumvents this problem, although it still leads to an extended simulation time by a factor N_R. However, the fact that the calculations are decoupled allows for parallel calculations on multiple processors. In Van Essen et al. (2006) the ensemble of reservoir models consisted of a number of hand-drawn geological realizations. In Sarma et al. (2005b) the optimization was performed in combination with a stochastic technique to quantify reservoir uncertainty in terms of approximate moments of the probability density functions of the uncertain reservoir parameters. Alternative techniques for robust optimization, without the need for implementation of an adjoint formulation, are based on the streamline-based sensitivity method, see Alhuthali et al. (2008), or on the use of an ensemble-based approximate gradient, a technique named the EnOpt method; see Chen et al. (2008).

Data assimilation

Adjoint-based techniques

Minimization of the objective function (9) for data assimilation is usually performed with the aid of an adjoint-based method; see e.g. Chavent et al. (1975), Li et al. (2003), Rodrigues (2006) and Oliver et al. (2008). It is possible to also take into account the uncertainty in the states with the aid of the 'representer method', which was first introduced in ocean engineering; see Bennett (2002). For early applications to reservoir engineering, see Przybysz-Jarnut et al. (2007), Rommelse et al. (2007), and Baird et al. (2007). It can be shown that for linear systems, and assuming Gaussian measurement and process noise, the representer method results in exactly the same answers as the, much older, Kalman smoother which will be briefly discussed below.

Ensemble Kalman filtering

Just as was the case for flooding optimization, a major disadvantage of adjoint-based data assimilation is the large programming effort required to implement the adjoint equations. This is the major reason for the recent rapid increase in popularity of the Ensemble Kalman Filter (EnKF) which can be implemented relatively easy 'around' an existing reservoir simulator. Kalman filtering was originally developed to estimate uncertain states, and not parameters, in linear dynamic systems from noisy measured data. Assuming Gaussian distributions for the uncertainty in the prior states and the measurements, posterior estimates for the states and the corresponding uncertainties can then be computed with the aid of closed-form matrix expressions. For nonlinear problems, of which parameter estimation problems form a subset, the ordinary Kalman filter breaks down because the nonlinearity results in non-Gaussian noise when propagated through the system. In the EnKF the analytical error propagation is replaced by a Monte Carlo approach, in which the model error covariance is computed from an ensemble of models which are all propagated in time. In analogy to the ensemble-based flooding optimization approach discussed above, the EnKF can be interpreted as a way to compute an approximate gradient based on a statistical relationship (cross-covariance). In this case the relevant cross-covariance is the one between the uncertain states and parameters, and the measurements; see Zafari and Reynolds (2007). The EnKF method has proved to be very successful in oceanographic applications where very large models, containing millions of state variables, are frequently updated using a variety of data sources; see Evensen (1994, 2007). During the forecast step a simulation is run for each of the models up to the time where new measurements become available. All models are updated by combining the new real measurements with forecasted measurements from the ensemble. Recently a large number of publications have appeared that apply the EnKF to reservoir engineering problems; see e.g. Nævdal et al. (2005) and Wen and Chen (2006) for early applications and Evensen (2006) and Gu and Oliver (2007) for recent overviews. These reservoir-focused implementations of the EnKF also treat parameters as unknowns, which leads to the use of an extended state vector $\hat{\mathbf{x}} = [\mathbf{x}^T \quad \boldsymbol{\theta}^T]^T$. Model updating using the EnKF relies on the cross-covariance between the measurements and the (extended) state. However, because the EnKF uses a low-order representation of the cross-covariance matrix, based on a relatively small ensemble, spurious updates may occur. Various 'localization' schemes are therefore being investigated to restrict updates to regions close to the measurements; see e.g. Devegowda et al. (2007). Another aspect of the EnKF is that it is well suited for sequential model updates which makes it a natural data assimilation technique for 'on-line' tracking of dynamic processes in 'real time', i.e. at the moment that new data become available. For reservoir engineering applications, however, this is not a major benefit because the processes involved are usually slow enough to allow for 'off-line' assimilation of a set of measurements over the entire history matching period. Moreover, the nonlinearity in the processes often requires repetition of the sequential data assimilation to improve the consistency between the updated parameters and dynamic response, see e.g. Reynolds and Zafari (2006) and Gu and Oliver

(2007). Although the Kalman filter differs from variational methods in that it updates states and parameters sequentially, it can be modified to adapt states and parameters at earlier moments in time, in which case it is known as a Kalman smoother. In fact, it can be shown that for state estimation in linear systems the representer method and the Kalman smoother lead to exactly the same results. For nonlinear systems this is not the case, and the methods will in general lead to somewhat different results.

Other techniques

Several other computer-assisted history matching methods have been developed in the reservoir engineering community using, e.g., streamline simulation to rapidly derive sensitivities of saturation changes along streamlines (Vasco et al., 1999), simulated annealing or genetic algorithms (Schultze-Riegert et al., 2002), or techniques to specifically honor geostatistical constraints, such as the gradual deformation method (Roggero and Hu, 1998) and the probability perturbation method (Caers, 2003). In addition, methods that emphasize the quantification of uncertainty have been developed such as semi-analytical techniques (e.g. Sarma et al., 2005b) the neighborhood algorithm (Erbaş and Christie, 2007) and Markov Chain Monte Carlo simulation (e.g. Barker et al., 2001). Especially the latter, stochastic, methods require a very large number of reservoir simulations, an approach that is usually computationally too demanding for practical purposes. This has lead to techniques to perform uncertainty assessment with the aid of upscaled models or 'proxy' models in the form of polynomial response surfaces that are derived from a limited number of simulations using an experimental design approach, see e.g. Omre and Lødøen (2004), Yang et al. (2007) and Alpak et al. (2009).

Reparameterization and model reduction

In our parameter and state estimation problems we are dealing with a very large number of 'inputs' (parameters and states) that need to be adjusted to obtain a best match between predicted and measured output. A typical reservoir model may contain millions of unknown parameters, such as grid block permeabilities and porosities, fault transmissibilities and initial conditions. Fortunately most of these parameters display spatial correlations that can be used to reduce the dimension of the parameter space, and various techniques to regularize the parameter estimation problem have been proposed using, e.g., zonation, wavelets (Sahni and Horne, 2005), Karhunen-Loève decomposition and its nonlinear version the kernel PCA (Sarma et al. 2007), or the discrete cosine transform (Jafarpour and McLaughlin, 2007). It has been shown that it is also possible to make use of spatial correlations in the states (pressures, saturations) to reduce the order of reservoir models using system-theoretical techniques, but application of these possibilities in optimization, data assimilation or upscaling has hardly yet been pursued. For some early attempts, see Heijn et al. (2004), Van Doren et al. (2006), Markovinović and Jansen (2006), Gildin et al. (2006), Vakili-Ghahani et al. (2008) and Cardoso et al. (2008).