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Real-time production optimization and reservoir management at the IO center

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Abstract: This paper presents research results within real-time production optimization and reservoir management at the Center for Integrated Operations in the Petroleum Industry (IO center). This includes life-cycle and long term issues like well location and target production rates. Further, results on short term production optimization, for instance the allocation of target production between wells and routing of wells into pipelines, will be presented. Finally, results on value chain optimization, where the production chain from reservoir to export is modelled, are reviewed.

Keywords: Production optimization, reservoir management, optimization

1. INTRODUCTION

Development of oil and gas fields require planning on several horizons. On a long term horizon, typically from some years to a field's lifetime, strategic reservoir planning is based on market conditions, field properties, available technologies and economic analyses. For an offshore field, decisions include concept choice such as FPSOs (Floating production storage and offloading) versus a complete or partial subsea solution, whether to process the fluid onshore or offshore, and export alternatives using pipelines or ships. During early field development it is important to plan, drill and commission new wells to reach a pre-defined plateau rate as soon as possible to generate a significant revenue stream. During the plateau production stage there may be an additional drilling program for production and injection wells. This involves decisions on the location and completion of wells. On an individual well level artificial lift technology may be applied to prolong well lifetime and thereby increase production. Injection strategies are critical to obtain high recovery. Injection fluids may range from water and gas to chemical injection fluids which lower the capillary pressure which prevents oil droplets from moving through a reservoir. The extraction of oil and gas from a reservoir resembles a batch process and there is a growing interest in applying closed loop reservoir management to increase recovery and thereby. Two overviews are provided in [Jansen et al., 2008] and [Foss, 2012].

A conventional multi-level control hierarchy as shown in **Figure 1** is well suited to structure decisions and control on different time horizons, see also [Saputelli et al., 2006]. Long term decisions are placed in the two upper boxes and information on some typical decision variables are included on the right hand side of the figure.

A typical offshore production chain, or value chain, is shown in **Figure 2,** the source being one or several subsurface reservoirs. Well streams are collected into a subsea pipeline system which feeds into a topside process system. The process system will typically consist of a liquid handling and a gas handling part. Its goal is to separate the reservoir fluid into light hydrocarbon components (natural gas) and liquid hydrocarbons, and remove other components like water, sulphur and CO_2. An important trend is that subsea production facilities are becoming more and more complex. First, the number of wells and tie-ins are increasing, and pipeline layouts are becoming increasingly complex. Second, smart wells are becoming more common, and third, topside process equipment like separators, pumps and compressors are being placed on the seabed. To elaborate on this there is an increasing number of smart wells being commissioned on complex high-producing wells. These wells may have several downhole valves to control the inflow in different well sections, see e.g. [Goh et al., 2008]. Further, multi-branch wells with independent branch control are popular in some assets. Finally, smart wells usually carry more downhole sensors than conventional wells. In all, the potential for control applications is increasing rapidly as smart wells are being deployed on a wider scale.

Returning to **Figure 1** and considering level 3, shorter time horizon decisions, typically from days or weeks and downwards, are considered. This includes the real-time production optimization (RTPO) problem where production may be constrained by reservoir conditions such as pipeline capacity or downstream conditions such water handling capacity on the process side. Hence, RTPO may require modeling of both the sub-surface part (reservoir and wells) and the surface part (pipelines and process facilities) of the value chain. Decision variables in RTPO include production and possibly injection rates, i.e. how to allocate production and injection between wells, and routing of well streams between pipelines. The goal may be to maximize daily production rates or to keep production at some pre-specified target rate. Overviews on RTPO can be found in [Bieker et al., 2006] and [Saputelli et al., 2005].

Below the dotted line in **Figure 1** closed-loop controllers are used for many purposes. This includes conventional level, flow and pressure control. There is also a growing interest in applying Advanced Process Control (APC) concepts. This is partly inspired by successes in downstream applications, see for instance [Qin and Badgwell, 2003]. Technologies are being developed for selected applications in production and drilling. Examples include slug control which essentially is a stabilizing problem, managed pressure drilling and coning control. These application areas will be discussed later. A recent survey of process systems methods in oil and gas fields is available in [Saputelli et al., 2005].

The Center for Integrated Operations in the Petroleum Industry (IO center) [NTNU, 2007] conducts research within integrated operations to promote increased oil recovery, accelerate production, reduce operating costs and improve safety and environmental standards. IO essentially means taking advantage of advanced information and communication technologies (ICT), collaboration tools and standardization. Central to this is placing real-time data into automatic as well manual decision loops and the use of advanced analyses techniques as part of this. The term IO is closely linked to Norwegian Continental Shelf activities and it goes by other names like i-field in Chevron, Digital Oil Field at Baker Hughes, Smart Fields in Shell, Field of the Future in BP, Smarter Oilfields in IBM and Digital Energy with Schlumberger. The IO center has 14 partner companies and the current plans continues until the end of 2014.

The goal of the paper is to present research results within real-time production optimization and reservoir management at the IO center. Section 2 will home in on life-cycle and long term issues with emphasis on closed-loop reservoir management (CLRM) while section 3 discusses RTPO. This includes the allocation of a target production rate between wells and routing of wells into pipelines. Section 4 centers on value chain optimization where the production chain from reservoir to export is modelled. Section 5 ends the paper with some concluding remarks. References are chosen to illustrate selected results and should not be understood as a complete list of references within these fields.

2. CLOSED LOOP RESERVOIR MANAGEMENT

CLRM research at the IO center includes modeling, control and optimization techniques as well as the Norne benchmark case.

Gas coning control has been a research topic initiated by collaboration with the Statoil Troll oil operating team. Gas coning is a tendency of the gas to drive the oil downward in an inverse cone contour toward a horizontal well. Once the gas reaches the well, gas production will dominate the well flow and the oil production will hence decrease, see **Figure 3**. Therefore, there is an incentive to maximize oil production until gas breakthrough. In [Hasan et al., 2010] and [Hasan et al., 2011b] the gas coning process in a gas oil reservoir completed with a single horizontal well is modeled, simulated, and analyzed applying a nonlinear control approach. The horizontal well model which describes the interaction between the well and the reservoir may be cast into a boundary control problem of the porous media equation with two boundary conditions; a Neumann boundary condition describing a no flow boundary at the outer boundary of the reservoir, and a nonlinear boundary condition describing the well production rate. A well rate controller for the boundary control problem is designed using the Backstepping method and analyzed by the Lyapunov method. The controller holds some formal performance guarantees and requires information on the gas oil contact at the well heel only. Further, the controller has a tuning parameter which can be used to maximize a suitable performance measure, e.g. Net Present Value. In a recently submitted paper [Hasan et al., 2011a] the method is evaluated using a detailed ECLIPSE simulator of gas coning wells. Simulation results confirm improvements compared to a conventional method where a constant rate is used up until gas breakthrough is detected.

Adjoint-based gradient computations for oil reservoirs have been increasingly used in CLRM optimization. Most constraints in the optimizations are for the control inputs, which may be (linear) bound constraints and equality constraints. In [Suwartadi et al., 2011] an interior barrier function approach is proposed to address (nonlinear) output constraints. This implies that the output constraints are added as a barrier term to the objective function to handle output constraints, e.g. an upper bound on the water saturation in a production well. Three case examples are presented. The results show that the proposed method is able to preserve the computational efficiency of the adjoint methods in the sense that the increase in computations is quite limited compared to the standard case without output constraints. In [Suwartadi et al., 2010] adjoints are used to compute second order information. These are used in a trust-region method and subsequently compared with a quasi-Newton approach using gradient information obtained by adjoints. The study indicated that there is little to be gained by computing second order information using adjoints compared to obtaining second order information in a conventional way by for instance using a BFGS algorithm based on first order information only.

Flexible modeling schemes and fast simulators is a key to realize CLRM. Multiscale modeling [Aarnes et al., 2008] is a promising approach which is researched within the IO center and which allows flexibility in terms of geological resolution since the grid for solving the pressure equations and the flow equations are decoupled. Further, multiscale modeling can be used for model reduction to derive proxy models suitable for optimization [Krogstad et al., 2011]. Within the IO center fast simulation techniques are combined with state of the art reservoir visualization software to demonstrate the power of embedding fast simulators into visualization tools. The prototype focusses on well screening, i.e. the workflow for selecting the location, the trajectory and the perforated zone of a new well. The fast simulator, in this case based on a Galerkin method [Natvig and Lie, 2008], provides an almost instantaneous measure of the new well's effect on ultimate recovery. Such a tool can hence be used to select promising candidates for later in-depth analyses.

Joint optimization of well position and control settings is a challenging problem with a significant potential as opposed to a conventional approach where these problems are solved in sequence. Because the nested problems have different characteristics they are addressed with different optimization methodologies. Well locations are optimized using (deterministic) derivative-free methods based on a pattern-search approach. These methods do not require gradient information, and are relatively easy (non-invasive to simulator code) to implement in distributed frameworks. Control optimization is solved by a sequential quadratic programming (SQP) implementation. Gradients are efficiently computed through an adjoint procedure. Present results using GPRS (Stanford's General Purpose Reservoir Simulator) are promising. The method and results are documented in a recently submitted paper [Bellout et al., 2011].

The Norne benchmark case is a one of a kind integrated data repository. The Norne licence, operated by Statoil ASA, has given the IO center access to the complete production history, 4D seismic survey data, reservoir description and models as well as detailed information on wells and well logs of the Norne field. This package, together with background information, is available through a portal on the IO center web pages [NTNU, 2007]. The idea is to provide the Norne data set to researchers to enable a fair comparison of CLRM methods, in particular methods for history matching and production optimization. To facilitate this the IO center and SPE hosted an Advanced Technology Workshop in June 2011. The main results of the workshop are documented in [Rwechungura et al., 2012]. The IO center will continue to support the Norne benchmark case.

Some results are emerging on analyzing closed loop performance as a whole rather than individual parts like data assimilation or production optimization by themselves. In [Foss and Jensen, 2010] performance limitations, in particular the detrimental effect workflow induced time-delays may have on performance, are studied. This makes sense since such time-delays can be managed by the way work is organized and distributed in an organization.

3. REAL-TIME PRODUCTION OPTIMIZATION

RTPO research at the IO center mainly adresses modeling, control and optimization challenges.

The well production and routing problem has been adressed in a series of papers. In [Foss et al., 2009] a method based on Lagrangian Decomposition (LD) for real-time well production and optimization is proposed. It exploits the pipeline architecture, and it piecewise linearizes the nonlinear well models and pressure drop pipeline models. This results in a highly efficient Mixed-Integer Linear Program (MILP) formulation. Further, the solution comes with a duality gap, i.e. a quality measure of the solution. This reasearch was triggered by discussions with and challenges raised by the Statoil Troll oil organization. The approach was further improved and thoroughly described in [Gunnerud and Foss, 2009] in which realistic models of gas coning wells like the Troll oil wells were used. Such behaviour complicates matters considerably since the models may be severely nonlinear and time-varying. It was shown that a Dantzig-Wolfe Decomposition (DWD) approach was superior to LD for two reasons. First, DWD was faster than LD. More important, however, was the fact that DWD was more robust in the sense that it works well on a wide variety of data sets without varying internal algorithm parameters. The results indicated a speedup of more than 100 times for both DWD and LD compared to a conventional solution method. In [Torgnes et al., 2011] a parallel implementation of the DWD algorithm was explored. Compared to the earlier sequential DWD implementation, the parallel implementation reduces solution time substantially as multiple CPUs are utilized to solve the subproblems concurrently. It was further shown how the parallel implementation could be designed in order to obtain an efficient utilization of the available parallel resources. The piecewise linearization approach is also applied to the petroleum production and routing problem at the Petrobras Urucu field in a recent paper submission [Codas et al., 2011]. In this latter work decomposition is not applied since the different parts of the pipeline network is more inter-connected than in the Statoil Troll oil case.

Workflow implication of the decomposition approach was discussed in [Gunnerud et al., 2010]. The decomposition method presented above has some merit beyond computational efficiency. It also provides a cost on the use of scarce resources, through the dual variables, which in the Troll oil case is gas capacity. This makes a solution more transparent since it helps to explain why a given solution makes sense and is a benefit of the approach that extends beyond RTPO. There are also other similar applications, for instance production optimization on a field level with several production units, import from distant satellite assets, and export through pipelines or by ships with a decentralized structure and few global constraints.

Transparency in terms of the cost of scarce resources comes in addition to the duality gap which clearly is of interest to any user. Such features may be important in modern offshore organizations which include at least one onshore team in addition to an offshore platform-based team. These teams are well connected through frequent videoconference meetings and other collaboration tools and common workflows. RTPO as discussed in the above papers mainly resides with the onshore team who performs analyses and makes recommendations to the offshore team where the final decisions are made and implemented. The daily workflow for a production engineer typically starts with a review of production and individual well performance. Sometimes it is also necessary to act on an abnormal situation, for example an underperforming well. Later during the morning, videoconferencing may be used to discuss and agree on the current situation, and make or adjust plans and production goals for the next 24 hours. In terms of content this meeting extends far beyond RTPO and include light maintenance, logistics, reservoir issues and drilling. The production engineers need to analyze the current situation and recommend a production strategy for the next day. This may require analyses on an individual well level, cluster level as well as the complete system. Hence, an optimization-based tool for allocation and routing needs to fit into the daily workflow of the onshore production engineers and be flexible in the sense that it can be integrated into similar analytical tools. An important part of this work is the updating procedures of the well and pipeline models, which are essential to maintain the quality of the optimization-based tool.

In a recent paper by [Grimstad et al., 2012] a partly derivative-free optimization algorithm for production optimization of a simulated multi-phase flow network is proposed. The network consists of well and pipeline simulators, considered to be black-box models without available gradients. The algorithm utilizes local approximations as surrogate models for the complex simulators. A mixed integer nonlinear programming (MINLP) problem is built from the surrogate models and the known structure of the flow network. The core of the algorithm uses IBM's MINLP solver Bonmin, which is run iteratively to solve optimization problems cast in terms of surrogate models. At each iteration the surrogate models are updated to local data points from the simulators. The algorithm is tested on an artificial subsea network modeled in FlowManager, a multi-phase flow simulator by FMC Technologies AS. The results for this special case show that the algorithm converges to a point where the surrogate models fit the simulator, and they both share the optimum.

4. VALUE CHAIN OPTIMIZATION

Operation of a production system as sketched in **Figure 2** may benefit from a holistic view of the value chain. This is particularly important if the different parts of the value chain are tightly connected. Present industrial practice typically takes a silo approach in the sense that one part of the supply chain is treated quite separately from other parts. This is pronounced in the upstream area where for instance a decision support application for optimally allocating well production may include well and pipeline models only. The downstream boundary condition is typically a constant pressure at the inlet separator. Similarly an optimizer for the surface process does not include models of the upstream system. This implies that the inlet separator acts as a dividing wall between two optimizers even though the two subsystems may be tightly connected.

In [Foss and Halvorsen, 2009] the value chain of the Snohvit offshore and onshore LNG system was modelled by simple models for each system component. This included wells, pipelines, and onshore separation and liquifaction units. The models were validated using a high-fidelity simulator. The simple models were used in an optimization tool and tested on a scenario with delayed ship arrivals. The key result was reduced losses when solving the production planning optimization problem as one system compared to the normal approach where the offshore and onshore systems were optimized separately. The use of simple models facilitated a fast solution of the planning problem which in this case was cast as a nonlinear program.

In general there is reluctance towards highly integrated solutions due to the complexity of such applications. There are, however, benefits to be gained. A realistic benchmark of a tightly coupled system has recently been introduced as a means to compare integration options in terms of costs and benefits [Juell et al., 2009, Rahmawati et al., 2012]. The benchmark is suitable for assessing the potential of integrated optimization because the upstream and downstream parts of the model are tightly coupled. The field asset model provides long-term production forecasts of gas, oil, and NGL revenue. All aspects of the model are realistic and well suited for both life-cycle analysis and shorter time-frame studies. The model is implemented in state-of-the-art software. Detailed documentation is made available so alternative software platforms with the necessary functionality may be used to study the same multi-field, integrated asset system. Such a benchmark may provide a credible reference for comparing alternative solutions, in particular the potential gain of integrating reservoir and process utilities into one optimization application. The complete documentation of the benchmark is available on the IO center web-pages.

The recent success of shale gas production relies to a large extent on drilling of long horizontal wells and efficient stimulation with multistage hydraulic fracturing. This practice typically leads to an initial peak production with a successive rapid decline followed by low and erratic production rates. In [Knudsen et al., 2012] shut-ins are proposed as a means to prevent liquid loading and boost late-life production rates from shale gas wells. The paper proposes a mathematical optimization scheme for production optimization of shale gas wells with the objective of maximizing short term production and long term recovery. The optimization problem is formulated as a full-space mixed integer linear program (MILP) using a separate dynamic proxy reservoir model and well model for each well. Each well model contains one time-dependent decision variable which defines at which times the well is either shut-in or producing. As a supplement to commissioning and drilling of a large number of new wells, the production optimization scheme proposed in this paper is a possible novel direction for enhanced utilization of shale gas wells that are in a late-life phase and producing at low gas rates.

5. CONCLUSIONS

Results which have a significant potential for improved recovery, accelerated production and reduced costs in petroleum production have been presented.

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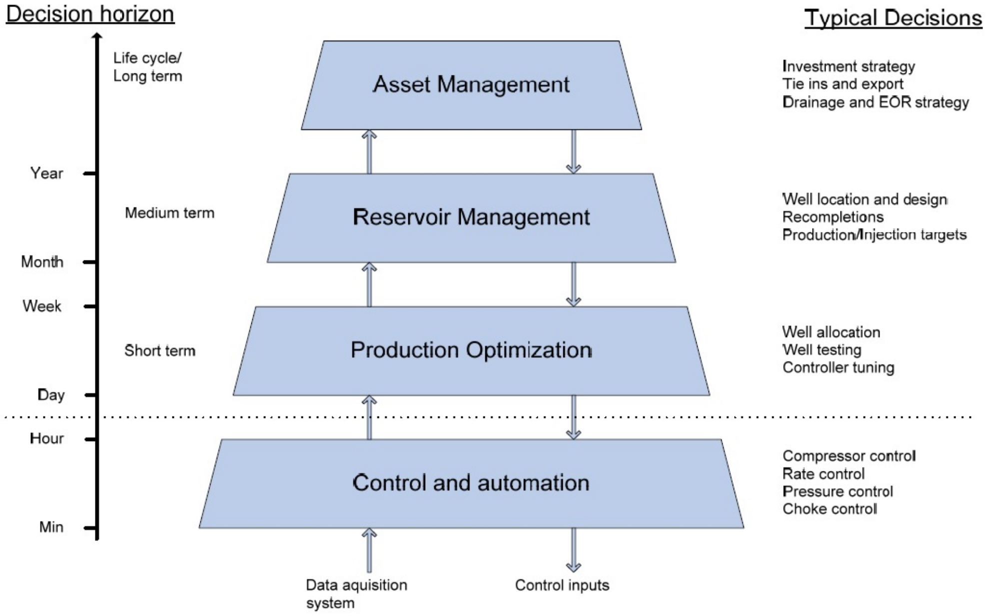

Fig. 1. Multi-level control hierarchy.

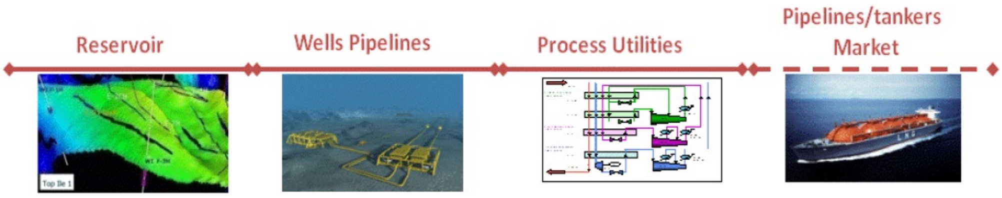

Fig. 2. Upstream value chain from reservoir to export.

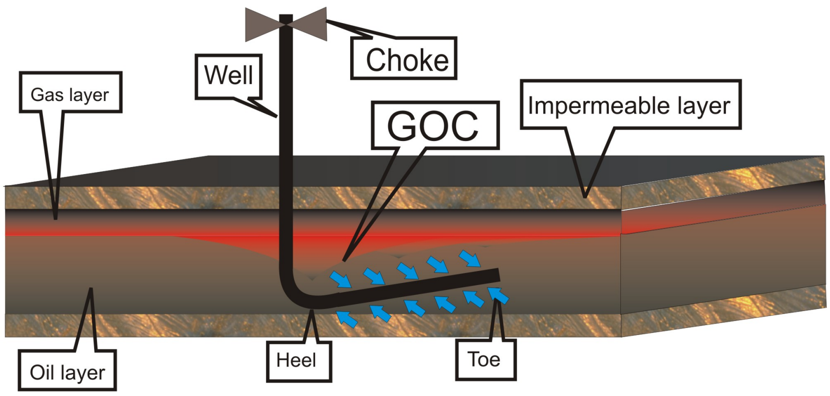

Fig. 3. Schematic view of a horizontal well which produces from an oil layer which is prone to gas coning. The gas layer will in practice be much thicker than shown in this sketch. There is water below the thin oil layer. GOC is short for Gas Oil Contact.