DISTRIBUTED OPTIMIZATION AND CONTROL OF OFFSHORE OIL PRODUCTION: THE INTELLIGENT PLATFORM

Michael R. Wartmann[a], Vidar Gunnerud[b], Bjarne A. Foss[b] and B. Erik Ydstie[a,*]

[a]Department of Chemical Engineering, Carnegie Mellon University, Pittsburgh, PA 15213, USA

[b]Department of Engineering Cybernetics, Norwegian University of Science and Technology, NTNU, 7491 Trondheim, Norway

Abstract

We describe a novel approach to distributed optimization and control of offshore oil production systems. The model incorporates a complex pipeline network. Oil and gas production systems are represented as a network of connected hierarchical structures of sub sea wells, manifolds and clusters. We consider multiphase flow of water, gas, and oil in the pipelines, and account for discrete switching and typical inflow characteristics of the sub sea wells. Network methods based on variational calculus provide a modeling framework for decentralized optimization and control. Conservation laws and the second law of thermodynamics combined with the passivity theory of nonlinear control lead to conditions for stability and optimality. We describe interconnections in networks through matrix representations that capture a network's topology. Control strategies are derived from the model, and stability and convergence to the optimal solution follows from the passivity conditions. The proposed distributed controller network can be seen as a special case of a Multi Agent System (MAS).

Keywords

process control, oil production, network theory, irreversible thermodynamics, distributed control, passivity, agents, Lagrangean decomposition, production optimization, multiphase flow.

Introduction

Information technologies and innovative hardware solutions provide novel opportunities for systematic reservoir management. Downhole sensors and remotely operated wells in combination with advanced software for data processing combined with oil reservoir models allow for monitoring and control of reservoir fluid dynamics. Application of advanced optimization and control techniques give improved production (Jansen, 2007).

However, reservoir management includes complex decision making on different hierarchical levels. Time scales range from real-time production optimization on an hourly or daily basis to long-term decisions on drainage strategies where the life-time of an asset comes into play. The complexity of decision-making for a large production system exceeds by far the magnitude in which an all-encompassing global optimization problem can be formulated and solved. Although model-based optimization algorithms are utilized to some degree, the state of the art in operations of oil and gas fields still relies on heuristics. Valuable resources are lost because of poor coordination (Kosmidis, 2005).

In order to operate oil and gas fields in a systematic and close to optimal manner, the optimization problem has to be separated into different time and length scales and hierarchical levels. Saputelli et al. (2005) developed a two-level reservoir management approach with supervisory optimization of the reservoir, wells and collection system connected to a decentralized controller network. Kosmidis et al. (2005) formulated an MINLP model for daily well scheduling. The nonlinear reservoir behavior, fluid flow in wells and pipelines and constraints from well, pipelines and the surface facilities of the platform are simultaneously considered.

In this paper, we address how the network character of oil and gas fields can be exploited to decompose the system into subsystems that self-optimize as a result of underlying topological properties of the network. We apply methods of decentralized control to achieve close to optimal conditions, where the approach can be viewed as a multi agent system. The advantage of the proposed approach lies in its generality and flexibility. Human decision makers, optimization and control algorithms, and intelligent software agents for data acquisition and communication can be interchanged and adapted as long as certain passivity conditions are satisfied while the total system also adapts and self-optimizes.

Problem Statement

Reservoir management for integrated oil and gas production systems can be decomposed into levels corresponding to different time horizons (Saputelli et al., 2005):

- Strategic Planning (years/lifetime)
- Tactical Reservoir Management (days/months)
- Real Time Production or Short-term Optimization (hours/days).

The structure of a typical petroleum production system is given in Fig. 1. It consists of (i) a reservoir, (ii) production wells, (iii) manifolds, (iv) flow lines to the surface, and (v) a first stage separator at some surface facility. The system may be larger with for instance several clusters. Each well consists of three parts: The well tubing, the choke, and the well flow line.

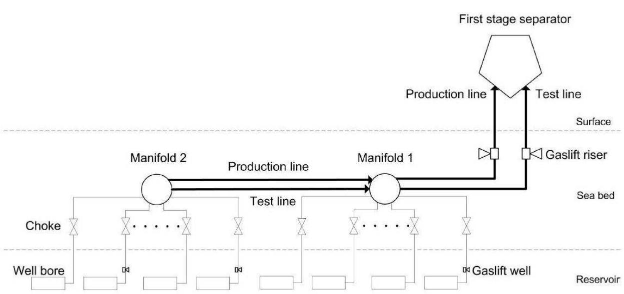

Figure 1. Topology for a typical oil and gas production system.

In Fig.1 well flow may be routed to one out of two flow lines. Further the production from a well may be controlled by a production choke valve. An oil and gas field typically consists of a large number of productions systems of the kind described here. These systems connect into one or more reservoirs at one end and the market at the other.

Network Theory

Network theory is well suited to model and analyze systems exhibiting a complex topological structure of interconnected embedded systems. An embedded system is a physical system with actuators and sensors interconnected with decision makers and other embedded systems through physical flows and communication (Ydstie, 2002). Network theory exploits the two mathematical structures which underly all physical models: The kinematic structure which addresses the topology of the system and a dynamical structure which captures conservation and dissipation. These properties are very compactly combined by the so-called Tellegen theorem which we review below after the geometric and topological structures of the process network have been defined.

Definition 1: A network of vertices P_i, $i = 1,..., n_p$, $n_p + 1,\ldots, n_t$ consisting of nodes and terminals interconnected through edges F_i, $i = 1, ..., n_f$ with topology defined by the graph

G = (F,P)

is called a process network if:

1. The state of each node is described inventories Z_i.
2. Conservation laws for Z_i hold.
3. There exists a $\mathbf{C}^1$, concave and first order homogeneous function $S(Z_i)$, called the entropy and a distinguished inventory Z_i so that $w_i = \partial S_i/\partial Z_i > 0$.

Continuity allows us to define potentials at the nodes so that $w_i = \partial S_i/\partial Z_i$. A typical topology is shown in Fig. 2. Flow in all directions, including recycle is allowed and accounted for.

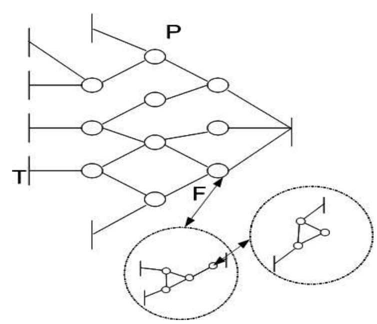

Figure 2. Graphical network representation: Topological structure of a network consisting of nodes P, terminals T, and flows F. Nodes can contain subgraphs and give rise to a hierarchical multiscale structure.

The process network can be seen as a flexible framework for modeling pipeline and reservoir systems. The topology represents the interconnection structure. Constitutive equations relate flow, production and terminal constraints to the potentials and define the dynamic relations of the flow connections by relating mass flow variables to the conservation laws through potential differences.

The Tellegen theorem is a purely topological result which is useful to prove stability and optimality of complex electrical circuits and networks. Jillson and Ydstie (2007) and Wartmann and Ydstie (2008) develop the generalization of Tellegen's theorem to multi-port process networks. A brief summary of the main result is given here.

Conservation Laws:

$$\frac{dZ_i}{dt} = \sum_{i=1, i\neq j}^{n_P} f_{ij} + p(Z_i) + \sum_{i=1}^{n_t} t_i, \qquad i = 1, ..., n_P \tag{1}$$

where f_{ij} denote internal flows, t_i terminal flows and p production. Continuity of the entropy gives the loop equations:

$$\sum_{loop} \Delta w_{ij} = 0 \tag{2}$$

The constitutive equations define the flow and production in terms of the potentials

$$f = \hat{f}(\Delta w)$$
$$p = \hat{p}(w) \tag{3a,3b}$$

Finally we have terminal constraints:

$$f_t = \hat{f}_t(t) \tag{4}$$

These can also be expressed as potential constraints ($w_t = \hat{w}_t(t)$). We then have the Tellegen theorem for process networks

$$\sum_{j=1}^{n_P} \Delta w_j \frac{dZ_j}{dt} = \sum_{k=1}^{n_f} \Delta w_k f_k + \sum_{j=1}^{n_P} w_j p_j + \sum_{j=1}^{n_t} w_j t_j, \qquad j = 1, ..., n_P + n_t \tag{5}$$

Passivity Theory and Irreversible Thermodynamics: Stability and Optimality

An operator $C : u \rightarrow y$ is said to be passive if there exists a storage function *V(t)*

$$0 \leq V(t) \leq V(0) - \int_0^t uy ds \tag{6}$$

Passivity theory provides a mathematical framework for the analysis of stability and control of networked process systems with nonlinear dynamics. The theory is particularly useful for systems for which explicit analytical models are not readily available, since they allow determining stability properties and robust control without a detailed model of the system. In fact a state description is not required (Desoer and Vidyasagar, 1975).

These results can be related to stability results in irreversible thermodynamics and the principle of minimum entropy production. The results show that if the operators which map potentials into flows are passive, the system naturally converges to state in which the entropy production is a minimum. It can also be shown, using variational calculus, that the system follows an optimized trajectory.

We now plan to develop a framework for managing the interconnection of decision makers and physical systems that exploit these results. The result can be understood from a physical point of view: For any valve setting the pipeline network chooses the path of least resistance for oil, gas and water flow by minimizing the dissipation losses. Consequently, if all chokes are open, one might infer that the total mass flow through the network is maximized. The problem then consists of modeling the system so that trade-offs between maximizing oil flow and simultaneously minimizing gas flow are managed properly to ensure longevity and high productivity of the field.

Network based oil platform model

The framework introduced in the previous section constitutes a basis for a network based model of the pipeline structure. The key component of the model is what we call the *interconnection superstructure* of the tree-like pipeline network captured by the *incident matrix* ***N***.

Definition 2: The node-to-branch incident matrix ***N*** is given for the matrix elements being

$$n_{ij} = \begin{cases} 1 & \text{if flow } j \text{ leaves node } i \\ -1 & \text{if flow } j \text{ enters node } i \\ 0 & \text{if flow } j \text{ is not incident with node } i. \\ y_{ij} & \text{if the flow } j \text{ to node } i \text{ can be switched on and off, } y_{ij} \in [0,1] \end{cases}$$

The incident matrix contains binary decision variables for the switching between flow lines y_{ij}. For a given *superstructure incident matrix* ***N***, we propose the following model based on Gunnerud and Litvak (2007):

Conservation laws:

$$\mathbf{N}\mathbf{q_o} = \mathbf{0}$$
$$\mathbf{N}\mathbf{q_g} = \mathbf{0}$$
$$\mathbf{N}\mathbf{q_w} = \mathbf{0} \tag{7a, 7b, 7c}$$

Pressure relations:

$$\mathbf{\Delta p} = \mathbf{N}^{\mathbf{T}} \mathbf{p_{abs}} \tag{8}$$

Reservoir to well inflow relations:

$$\mathbf{\Delta p}^{\mathbf{WELLBORE}} = f(\mathbf{q_o}, \mathbf{q_g}, \mathbf{q_w}) \tag{9}$$

Pipeline pressure drops (momentum balances):

$$\mathbf{\Delta p}^{\mathbf{PIPELINE}} = f(\mathbf{q_o}, \mathbf{q_g}, \mathbf{q_w}) \tag{10}$$

Choke pressure drops:

$$\mathbf{q_o} = f(\mathbf{d}^{\mathbf{CHOKE}}, \mathbf{\Delta p}^{\mathbf{CHOKE}}) \tag{11}$$

The conservation laws in vector form of Eq. 7 represent balances of the mass flow rates for oil $\boldsymbol{q_o}$, gas $\boldsymbol{q_g}$, and water $\boldsymbol{q_w}$ about every node in the pipeline network. The pressure relations ensure that the pressure decreases according to the pressure drops from the reservoir pressure $\boldsymbol{p}^{\boldsymbol{R}}$ to the separator pressure $\boldsymbol{p}^{\boldsymbol{S}}$ along each path or sum up around each closed loop through the network. Eqs. 7 and 8 represent the generalized Kirchhoff laws for the pipeline network. These equations are static and linear and constitute the topological relations of the network.

The multiphase flow in the pipelines is complex and nonlinear. The pressure drop and inflow relations are commonly described through empirical or semi-empirical models. The momentum balance in the pipelines is rather given in form of discrete performance tables or measured data than analytical functions (Litvak, 1995). Nonlinearities and dynamics of the system are introduced through Eqs. 9-11. The parameters $\boldsymbol{d}^{\boldsymbol{CHOKE}}$ are continuous control parameters to adjust the flows through the wells. Further constraints during operation are imposed by the equipment. These constraints are mainly capacity limits for the oil, gas and water flow in the pipelines and constraints imposed by the handling facilities at the surface. Boundary conditions for the model occur where the pipeline network is connected to the environment, i.e. the upstream boundary conditions apply as reservoir pressures for each well and the downstream the separator pressure are given at the terminals. The free variables available for control and optimization are the choke openings as well as the discrete switches for the flow lines.

Optimization using Agent Systems

The Tellegen theorem shows that we can approach the problems of stability and optimality of the network using distributed decision making since these properties are determined by decisions made at the node level. The question then becomes how to orchestrate these decisions so that relevant objective functions are optimized. In an attempt to move in this direction we draw inspiration from multi agents systems which display similarities to the ideas described above.

Important results concerning global optimality of the system with local selfishly acting agents are generally derived using game theory. We conceptualize a competitive system of agents playing non-cooperative games on each hierarchy level. The goal of each agent is to maximize the flow capacity that is assigned to it. The assignment of flow capacity is performed by a customer like agent on the next hierarchy level. The costumer agent functions as a competitive trader and competes with other agents for the flow capacities on the next higher level. Consequently, we develop a structure of agents similar to a classical business environment in a market economy. We explore structures of collaboration between agents across hierarchy levels and structures of competition for agents on the same hierarchy (Fig. 3). Cooperative behavior between the hierarchy levels plays a crucial role, since pure competitive behavior leads to a Nash equilibrium which can be far from optimal and lead to instabilities for strongly interacting systems (Rawlings, 2007).

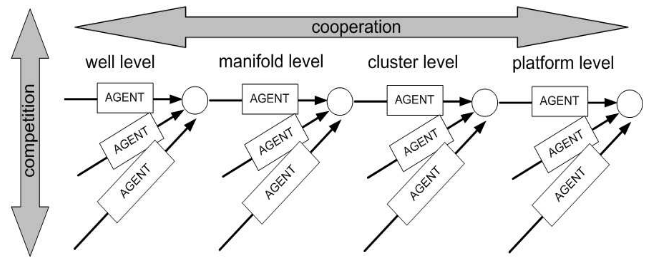

Figure 3. Structure of multi agents system.

The main advantage of the proposed agent system lies in its flexibility and versatility. The MAS can ultimately assist human decision making on the platform, simulate different scenarios and serve as an educational software tool for training purposes.

Conclusions

In this paper, we describe a network-based modeling approach for oil and gas production optimization of offshore fields. The network model's passive structures are explored to analyze stability and optimality properties of the system. We address the natural objective function that is minimized for the pipeline network converging into steady state condition using non-equilibrium thermodynamics. We propose an agent based decision making framework for decentralized control to integrate and merge human and machine decision making processes.

Acknowledgments

We acknowledge the support of the Center for Integrated Operations at NTNU, Norway.

References

Saputelli, L., Nikolaou, M., Economides, M. (2005), Self-learning reservoir management, *Society of Petroleum Engineers*.

Kosmidis, V. D., Perkins, J. D., Pistikopoulos, E. N. (2005), A mixed integer optimization formulation for the well scheduling problem on petroleum fields, *Comput. Chem. Eng.*, *29*, 1523

Ydstie, B. E. (2002), New Vistas for Process Control: Integrating Physics and Communication Networks, *AIChE J. 48*, 422

Kendell R. Jillson, B. Erik Ydstie (2007), Process networks with decentralized inventory and flow control, *J. of Proc. Control 17*, 399

Desoer, C. A., Vidyasagar, M. (1975), Feedback Systems: Input–Output Properties. *New York Academic Press.*

Jansen, J.D., (2007), Model-based control of subsurface flow, *DYCOPS 2007, Cancun, Mexico.*

Gunnerud, V., Litvak, E., (2007), Production Planning Optimization for the Troll C Field, *Master Thesis, NTNU, Trondheim, Norway.*

Rawlings, J.B., Stewart, B.T. (2007), Coordinating Multiple Optimization-based Controllers: New Opportunities and Challenges, *DYCOPS 2007, Cancun, Mexico.*

Wartmann, M.R., Ydstie, B.E. (2008), Optimality of Integrated Process Networks, *ACC 2008, Seattle, USA.*