Short-term Production Optimization of Offshore Oil and Gas Production Using Nonlinear Model Predictive Control

Anders Willersrud * **Lars Imsland** * **Svein Olav Hauger** ** **Pål Kittilsen** **

* *Department of Engineering Cybernetics, Norwegian University of Science and Technology, N-7491 Trondheim, Norway (e-mail: anders.willersrud@no.abb.com, lars.imsland@itk.ntnu.no).*
** *Cybernetica AS, N-7032 Trondheim, Norway (e-mail: {svein.o.hauger,pal.kittilsen}@cybernetica.no).*

Abstract: This paper describes how nonlinear model predictive control (NMPC) can be used directly for short-term production optimization in an offshore oil and gas platform.
Two methods for production optimization in NMPC are investigated. The first method is the *unreachable setpoints* method where an unreachable setpoint for oil production is used in order to maximize oil production. The ideas from this method are combined with the exact penalty function for soft constraints in a second method, named *infeasible soft-constraints*. These methods are used in a case study of offshore oil and gas production, where both methods find the economically optimal operating point. Their relative merits, and advantages compared to a two-layer structure, are discussed.

Keywords: Nonlinear model predictive control, production optimization, oil and gas production

1. INTRODUCTION

There are strong incentives for dynamic process operation with improved profitability, enhanced flexibility and reduced environmental footprints. As a response to this, there has been a trend, at least in academic literature, towards closer integration of process control and economic process optimization (e.g. Backx et al., 2000; Engell, 2007; Kadam and Marquardt, 2007; Rawlings and Amrit, 2009), to address perceived shortcomings of traditional multi-layer control structures. Such integrated approaches are sometimes called dynamic real-time optimization (DRTO).

As oil- and gas reserves become increasingly hard and expensive to explore and produce, there is a drive in the oil- and gas industry towards making use of optimization strategies of traditional process industries to ensure profitable operation (e.g. Bieker et al., 2006; van Essen et al., 2009; Saputelli et al., 2006).

The main objective in this paper is to study how dynamic real-time optimization in the form of nonlinear model predictive control (NMPC) can be used for short-term production optimization in an offshore oil and gas processing plant. While long-term production optimization strives to optimize net present value of the reservoir resources, short-term optimization is about optimizing daily production-rate (through-put) given the injection- and production strategies chosen by the long-term production optimization. Thus, short-term production optimization is similar to production optimization found in other process industries.

The study employs an industrial NMPC tool, and it is therefore focused on methods that can be implemented directly in such a package. It is assumed (with little loss of generality) that the production optimization objective can be cast as maximization of one (or more) of the controlled variables. Two methods will be studied; the use of unreachable setpoints (Rawlings et al., 2008), and infeasible soft-constraints. To the authors' knowledge, the use of the latter approach in an economic optimization setting is new.

The NMPC formulation used is presented in Section 2, and ways for direct production optimization are discussed, with emphasis on methods using unreachable setpoints and infeasible soft-constraints. In Section 3, a case study based on a fairly complex, realistic model of an offshore plant for oil and gas production is carried out. We end the paper with some discussion.

2. NONLINEAR MODEL PREDICTIVE CONTROL AND PRODUCTION OPTIMIZATION

In this section the NMPC formulation is presented, and production optimization is discussed, with emphasis on methods including economic optimization explicitly in the NMPC control objective.

2.1 NMPC formulation

The nonlinear model representation used for NMPC is on discrete form,

[1] Anders Willersrud is presently with ABB Process Automation division, Oil, Gas and Petrochemicals.

$$x_{k+1} = f(x_k, u_k, d_k), \tag{1a}$$
$$z_k = h(x_k), \tag{1b}$$

where $x_k \in \mathbb{R}^{n_x}$ are the states, $u_k \in \mathbb{R}^{n_u}$ are the inputs, $d_k \in \mathbb{R}^{n_d}$ are known (measured or estimated) disturbances, and $z_k \in \mathbb{R}^{n_z}$ are the controlled outputs.

We will use soft output constraints, and thus the augmented NMPC objective function is

$$\min_{\Delta u, \varepsilon} J_{\text{aug}} = \sum_{i=1}^{P} (z_{k+i} - z_{\text{ref}})^\top Q (z_{k+i} - z_{\text{ref}}) + \sum_{j=0}^{N-1} \Delta u_{k+j}^\top S \Delta u_{k+j} + \sum_{i=1}^{P} r^\top \varepsilon_{k+i} \tag{2}$$

where the input moves

$$\Delta u_k = u_k - u_{k-1} \tag{3}$$

and the output constraint violations $\varepsilon \in \mathbb{R}^{P \cdot n_z}$ are the optimization variables. The optimization is subject to the model (1) and

$$z_{\min} - \varepsilon_{k+i} \le z_{k+i} \le z_{\max} + \varepsilon_{k+i}, \quad i = 1, \ldots, P \tag{4a}$$
$$u_{\min} \le u_{k+j} \le u_{\max}, \quad j = 0, \ldots, N-1 \tag{4b}$$
$$\Delta u_{\min} \le \Delta u_{k+j} \le \Delta u_{\max}, \quad j = 0, \ldots, N-1 \tag{4c}$$
$$\varepsilon_{k+i} \ge 0, \quad i = 1, \ldots, P \tag{4d}$$

where $Q \in \mathbb{R}^{n_z \times n_z}$ and $S \in \mathbb{R}^{n_u \times n_u}$ are the weighting matrices of output and input moves, respectively, and the vector $r \in \mathbb{R}^{n_z}$ is the penalty weight for constraint violations.

Formulations employing soft output constraints via exact l_1 penalty functions are well-known from literature (de Oliveira and Biegler, 1994; Scokaert and Rawlings, 1999) and are used in some industrial NMPC systems (Foss and Schei, 2007). The main rationale behind its use is to avoid feasibility problems related to hard output constraints.

2.2 Production optimization

The control structure in a process plant is often divided into several layers separated by time scale, e.g. Skogestad (2004). The MPC may be located in a control layer, whereas a *real-time optimization* (RTO) system is a model-based system using steady-state models which can be located above the MPC in the control hierarchy, providing setpoints to the MPC. The two-layer approach has several advantages and is widely used. However, if a (nonlinear) process model with validity over the entire operational window is used, Engell (2007) argues that the two-layer approach can be replaced by a one-layer approach by augmenting or replacing a MPC quadratic tracking cost function with an economic cost function. On a general form, this cost function may be expressed as

$$J_{\text{eco}} = \sum_{i=0}^{P} \Phi(z_{k+i+1}, u_{k+i}). \tag{5}$$

Several advantages of such a scheme are listed in Engell (2007), including faster reaction to disturbances, exact constraints can be implemented for measured variables, all degrees of freedom can be used to optimize the process, also during transients, and inconsistencies between models are avoided. A disadvantage of using a one-layer approach is that the demands on the model used for dynamic optimization may be higher, typically implying increased computational demand.

Several authors, e.g. Rawlings and Amrit (2009), consider linear profit functions for NMPC with economic optimization, similar to

$$J_{\text{eco}} = \sum_{i=0}^{P} \left(a^\top z_{k+i+1} + b^\top u_{k+i} \right). \tag{6}$$

Here the cost is unbounded for an unconstrained problem. If using such an economic objective on a finite horizon, the result of the so called turnpike theorem can be observed. This effect is identified by a trajectory which spends most of the time at an equilibrium path, independent of initial value and final time. Under some conditions, this turnpike reduces to a singleton different from the equilibrium (Würth et al., 2009).

Other approaches can also be found in the literature, but we will here concentrate on two methods that are simple to implement in many "standard" MPC tools. First a method that uses unreachable setpoints, and then a method which in effect is similar to the linear cost function above, namely the use of infeasible soft-constraints.

2.3 Unreachable setpoints

A variant of the one-layer method is the use of unreachable (infeasible) setpoints by selecting high/low unreachable setpoints for the variables that should be maximized/minimized. This is a simple method that allows the inclusion of economic optimization in standard MPC tools. Use of the method is related to the practice (in linear MPC, at least) of using target calculation and a priority hierarchy (Strand and Sagli, 2004, e.g.) for doing production optimization in a single MPC layer, but to keep the discussion simple we will not dwell further on this here.

The use of unreachable setpoints is analyzed in Rawlings et al. (2008) for linear MPC, and conditions for stability and convergence are established. Moreover, MPC using unreachable setpoints is compared to a "standard" two-layer target-tracking cost function in two examples, and seen to result in considerable cost improvements under certain disturbance scenarios.

We will here formulate a setup where setpoint tracking is combined with unreachable setpoints, that will be used in the case study. Note that the discussion here is limited to a maximization problem, without loss of generality. Let $z^{\text{opt}} \in \mathbb{R}^{n_{z,\text{opt}}}$ be the CVs which should be maximized, $z^{\text{sp}} \in \mathbb{R}^{n_{z,\text{sp}}}$ be the CVs which should be held at (feasible) setpoints and $z^{\text{float}} \in \mathbb{R}^{n_{z,\text{float}}}$ be the CVs which only should be held within limits. The output vector can now be expressed as

$$z = \begin{bmatrix} z^{\text{opt}} \\ z^{\text{sp}} \\ z^{\text{float}} \end{bmatrix} \in \mathbb{R}^{n_z}. \tag{7}$$

The number of elements in z^{opt} and z^{sp} should be limited by the degrees of freedom, i.e. the number of MVs by

$$n_{z,\text{opt}} + n_{z,\text{sp}} \le n_u.$$

If $n_{z,\text{float}} > 0$, some of the CVs will not be included in the objective function making Q positive-semidefinite. With z defined in (7), Q will be

$$Q = \begin{bmatrix} Q_{\mathrm{opt}} & & \\ & Q_{\mathrm{sp}} & \\ & & 0 \end{bmatrix}.$$

The first part of (2) can now be written as

$$\begin{aligned}(z_{k+i} - z_{\mathrm{ref}})^\top Q(z_{k+i} - z_{\mathrm{ref}}) \\ = (z_{k+i}^{\mathrm{opt}} - z_{\mathrm{ref}}^{\mathrm{opt}})^\top Q_{\mathrm{opt}}(z_{k+i}^{\mathrm{opt}} - z_{\mathrm{ref}}^{\mathrm{opt}}) \\ + (z_{k+i}^{\mathrm{sp}} - z_{\mathrm{ref}}^{\mathrm{sp}})^\top Q_{\mathrm{sp}}(z_{k+i}^{\mathrm{sp}} - z_{\mathrm{ref}}^{\mathrm{sp}}),\end{aligned}$$

where $z_{\mathrm{ref}}^{\mathrm{opt}}$ are the unreachable setpoints used to optimize the corresponding controlled variables.

The contribution of the unreachable setpoint to the sensitivity $\frac{\partial J_{\mathrm{sp}}}{\partial \Delta u_j}$ of (2) is given by

$$(z_{k+i}^{\mathrm{opt}} - z_{\mathrm{ref}}^{\mathrm{opt}})^\top Q_{\mathrm{opt}} \frac{\partial z_i^{\mathrm{opt}}}{\partial \Delta u_j}, \tag{8}$$

and we thus see that both the values of $z_{\mathrm{ref}}^{\mathrm{opt}}$ and Q_{opt} will affect the solution. This might give rise to unexpected behavior during tuning and/or reconfigurations and change of operating points.

Cost functions using unreachable setpoints are unbounded on infinite horizons, and thus "standard" analysis of stability and convergence employing cost functions as Lyapunov functions can no longer be used. For linear MPC, analysis is provided in Rawlings et al. (2008), while results towards nonlinear systems can be found in Diehl et al. (2010).

2.4 *Infeasible soft-constraints*

The exact penalty function and infeasible soft-constraints can be used as a method for production optimization in a similar manner as unreachable setpoints. The discussion here is based on the exact l_1 penalty function (de Oliveira and Biegler, 1994).

We limit ourselves to maximization of positive variables, without loss of generality. Similar to (7), let $z^{\mathrm{opt}} \in \mathbb{R}^{n_{z,\mathrm{opt}}}$ be the CVs which should be maximized, and let $z^{\mathrm{rem}} \in \mathbb{R}^{n_{z,\mathrm{rem}}}$ be the remaining CVs. The output vector can now be expressed as

$$z = \begin{bmatrix} z^{\mathrm{opt}} \\ z^{\mathrm{rem}} \end{bmatrix} \in \mathbb{R}^{n_z}. \tag{9}$$

The basic idea is to select the lower constraint of z^{opt} larger than the maximum value that can occur, in other words, z^{opt} will always be infeasible according to this constraint. Thus, in (4a) we will always have

$$0 \le z_{k+i}^{\mathrm{opt}} < z_{\min}^{\mathrm{opt}} \le z_{\max}^{\mathrm{opt}},$$

and the lower bound on the constraint (4a)

$$z_{\min}^{\mathrm{opt}} - \varepsilon_{k+i}^{\mathrm{opt}} \le z_{k+i}^{\mathrm{opt}} \le z_{\max}^{\mathrm{opt}} + \varepsilon_{k+i}^{\mathrm{opt}}$$

will always be active. This means that the lower inequality can be written as

$$z_{\min}^{\mathrm{opt}} - \varepsilon_{k+i}^{\mathrm{opt}} = z_{k+i}^{\mathrm{opt}} \Rightarrow \varepsilon_{k+i}^{\mathrm{opt}} = z_{\min}^{\mathrm{opt}} - z_{k+i}^{\mathrm{opt}} > 0.$$

The last term of the cost function J_{aug} in (2) can now be written as

$$\sum_{i=1}^{P} r^\top \varepsilon_{k+i} = \sum_{i=1}^{P} r_{\mathrm{opt}}^\top \left(z_{\min}^{\mathrm{opt}} - z_{k+i}^{\mathrm{opt}}\right) + \sum_{i=1}^{P} r_{\mathrm{rem}}^\top \varepsilon_{k+i}. \tag{10}$$

We see that the cost function now contains the linear cost

$$-\sum_{i=1}^{P} r_{\mathrm{opt}}^\top z_{k+i}^{\mathrm{opt}}. \tag{11}$$

The sensitivity of the objective function with respect to the variables that we want to optimize is now independent of choice of $z_{\min}^{\mathrm{opt}}$ and the particular operating point, which can give easier tuning than the unreachable setpoint method. That is, the penalty weight r_{opt} is now a linear cost weight with similar effect as Q_{opt} has for unreachable setpoints, but it can be tuned independently of the value chosen for the infeasible constraint, and the effect is to some degree independent of operating point.

However, it should be noted that the choice of r_{opt} in relation to the choice of r_{rem} can be a delicate matter with significant impact on dynamics when some of the remaining output constraints are active. Also, strategies for complexity reduction might introduce 'blocking strategies' on the ε's in (4a) which will have an impact on the solution. This tuning problem is a matter for further investigation but will not be addressed in this paper.

Furthermore, if several outputs should be optimized it can be difficult to select good weighting values. In some cases it may be possible to specify a function $g(x, u)$ which represents the optimization objective, and add this function as a CV, namely $z = g(x, u)$.

Note that as in the previous section, the cost function will be unbounded on the infinite horizon, since in general $z_{\min}^{\mathrm{opt}} - z_{k+i}^{\mathrm{opt}} > 0$. In principle the methods of Diehl et al. (2010) can be used for stability and convergence analysis, if appropriate stability constraints are added.

3. SHORT-TERM PRODUCTION OPTIMIZATION OF OFFSHORE OIL AND GAS PRODUCTION

The main objective of an offshore processing plant is to transport and separate the oil, gas and water produced from a set of reservoirs and process oil and gas for export. On the sea-bed there can be a large number of wells ordered in clusters. Pipes transport the streams from the different wells and clusters through a network on the sea-bed to a production manifold. The production manifold can route the stream either to a test separator or to the first stage of a production separator train. We assume in this problem that the main product in terms of revenue is oil, and that gas has little direct value.

On a long term, the objective for process optimization is typically to maximize total recovery or net-present value of the total revenue. This is achieved by deciding which wells to produce from and how (routing), to what extent use water flooding, gas injection, etc., to make optimal use of the reservoir resources. Herein, this problem will not be considered and the routing and use of recovery methods will be considered fixed.

The topic in this paper is thus optimization of production rate given a chosen long-term strategy. This is often called a short-term optimization problem, where the problem can be considered time-independent (Díez et al., 2005; Awasthi et al., 2008; van Essen et al., 2009). A typical issue can be how to maximize oil production from the producing wells, which have varying (production dependent) gas, oil and water contents, under topside processing constraints (e.g. limited gas compression capacity).

This study concentrate on optimization and control, and important issues like state- and parameter estimation (model update) and robustness to model errors are considered outside the scope of this paper.

3.1 Case description

The case will be based on a model of a rather generic offshore oil platform. The model is developed using the Modelica-based advanced modeling software Dymola, using Cybernetica's in-house Modelica library for oil and gas production systems, named CyberneticaLib, along with components/interfaces from the Modelica Standard Library (in particular Modelica.Fluid). The model is developed having the integration in a real-time system in mind. Thus, it is not as complex as some process simulators, but complex enough to capture key process dynamics in an offshore processing plant. The resulting model includes multiphase flows through pipes and chokes, different gas/oil-ratios (GOR) in near-well models of reservoirs, a multiphase separator and a polytropic head relationship in the compressors. The reservoir models are time-independent, and are thus limited to the short-term scope studied in this paper. The model used in this case study has 249 dynamic states. Even though the model is fairly large, it is efficient enough to ensure that all NMPC optimization problems reported here are solved within real-time demands with a sample time of 1 minute.

A schematic overview of the model is shown in Figure 1. The overall structure is a set of clusters of wells which are mixed in a production manifold and fed to a separator train (topside process) that separate and process gas, oil and water. In each cluster there are one or two wells. The "Remaining Clusters"-part represents a lumped set of clusters each having several wells, but where we assume there is no control degrees of freedom. The conditions in this cluster are set such that the majority of the total production is produced here and that the typical total production is within typical values. The typical height from the clusters up to the manifold is 330 meters, and the depths from the well heads to the reservoir are set to be around 1200 meters.

The short-term economic objective is to maximize oil production within the plant's operating limits, by adjusting the production from the different active wells. That is, the cost function (5) can be written as

$$J_{\mathrm{eco}} = -\sum_{i=1}^{P} z_{\mathrm{oil},k+i} \tag{12}$$

where the (rate of change of) choke openings are the optimization variables.

Depending on both the plant and the stream from the reservoirs, limited processing capacities for either oil, gas or water can limit the production, but in many cases, including this one, gas processing capacity is the main limiting factor. A consequence of this is often that the pressure in the inlet separator tank will be an active constraint under optimal production, since this typically maximizes gas processing capacity. A simple approach to optimizing control could thus be to use a "squeeze and shift" (Seborg et al., 2004) strategy using a single well as a "swing producer" to keep the inlet separator pressure as close to the limit as safety allows.

However, in addition to be dependent on the gas production capacity, the total oil production depends on the GOR and the marginal GOR (MGOR) in the different reservoirs. If the total field gas rate reaches the plant capacity in a gas-limited plant with gas-coning wells, and there are no other active constraints, maximal oil production is achieved when all the wells have the same MGOR (Urbanczyk and Wattenbarger, 1994), that is,

$$\left(\frac{\partial Q_G}{\partial Q_O}\right)_i = \left(\frac{\partial Q_G}{\partial Q_O}\right)_j \qquad i, j = 1, ..., n \tag{13}$$

where $Q_G[\mathrm{Sm}^3/\,\mathrm{day}]$ is the gas flow, $Q_O[\mathrm{Sm}^3/\,\mathrm{day}]$ is the oil flow and n is the number of wells.

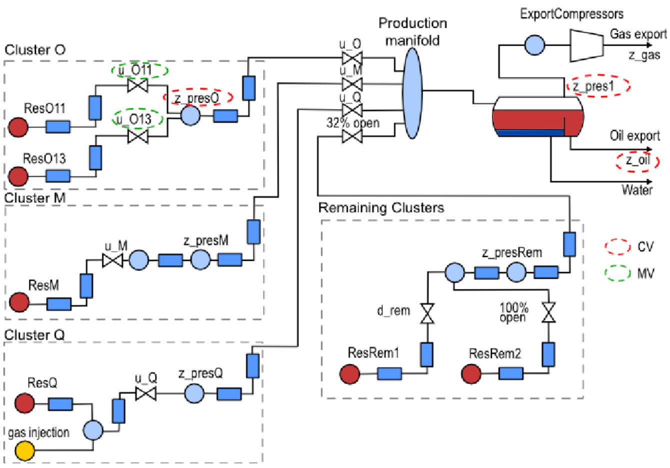

Fig. 1. Process overview.

In the following cases, the unreachable setpoints method and the infeasible soft-constraints methods are used to manipulate the two well chokes $u_{\mathrm{O}13}$ and $u_{\mathrm{O}11}$ in Cluster O to optimize total oil production. Indirectly, this implies finding the point where (13) is fulfilled, in addition to pushing the inlet separator pressure towards its constraint.

3.2 Using the unreachable setpoints method

Using the unreachable setpoints method as explained in Section 2, the CVs included in the MPC objective function are the line pressure z_{presO} in Cluster O, the inlet separator pressure z_{pres1} and the total oil production z_{oil} which represents the economic variable which should be maximized. In the given initial production setup, z_{pres1} is considered to be lying on the maximum safe operating point, which cannot be further increased. The objective is thus to alter the choke configuration

$$u = [u_{\mathrm{O}13}\ u_{\mathrm{O}11}]^{\top} \tag{14}$$

in order to further increase production, not violating this constraint.

With u from (14), there are $n_{z,\mathrm{opt}} + n_{z,\mathrm{sp}} = n_u = 2$ degrees of freedom for optimizing oil production and setpoint tracking. There are no specifications on setpoints for z_{pres1}

and z_{presO} other than that they must lie inside some limits, and hence $n_{z,\mathrm{sp}} = 0$ is used.

The setup used is given by

$$z = \begin{bmatrix} z^{\mathrm{opt}} \\ z^{\mathrm{float}} \end{bmatrix} = \begin{bmatrix} z_{\mathrm{oil}} \\ z_{\mathrm{pres1}} \\ z_{\mathrm{presO}} \end{bmatrix}; \begin{bmatrix} 100\,\mathrm{kg/s} \\ 19\,\mathrm{bar} \\ 40\,\mathrm{bar} \end{bmatrix} \leq z \leq \begin{bmatrix} 300\,\mathrm{kg/s} \\ 20.34\,\mathrm{bar} \\ 80\,\mathrm{bar} \end{bmatrix}$$

$$Q = \mathrm{diag}\{0.01,\, 0,\, 0\};\; S = \mathrm{diag}\{0.01, 0.01\};$$

$$r = \begin{bmatrix} 10^3 & 10^3 & 10^3 \end{bmatrix}^\top$$

$$\begin{bmatrix} -20\% \\ -20\% \end{bmatrix} \leq \begin{bmatrix} \Delta u_{O13} \\ \Delta u_{O11} \end{bmatrix} \leq \begin{bmatrix} 20\% \\ 20\% \end{bmatrix}; \begin{bmatrix} 10\% \\ 10\% \end{bmatrix} \leq \begin{bmatrix} u_{O13} \\ u_{O11} \end{bmatrix} \leq \begin{bmatrix} 100\% \\ 100\% \end{bmatrix}$$

The unreachable setpoint for z_{oil} is selected to be $z_{\mathrm{ref}}^{\mathrm{opt}} = 208.3\,\mathrm{kg/s} = 20\ 000\,\mathrm{Sm^3/day}$ which is large enough to always be infeasible, but not too large since together with the weight Q_{opt}, the difference $|z_{\mathrm{oil}} - z_{\mathrm{ref}}^{\mathrm{opt}}|$ will affect the gain. The MPC is activated at $t = 10\,\mathrm{min}$ and the responses are shown in Figures 2 and 3.

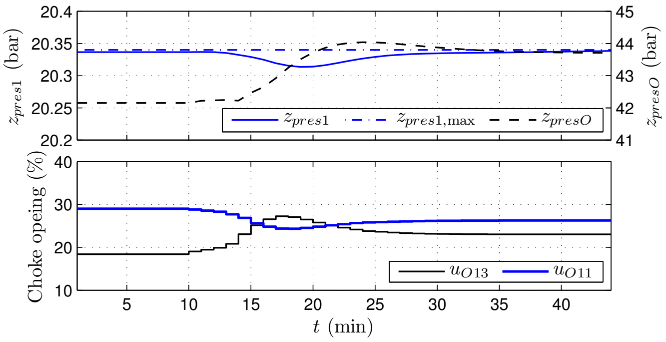

Fig. 2. Pressures and choke openings using unreachable setpoints.

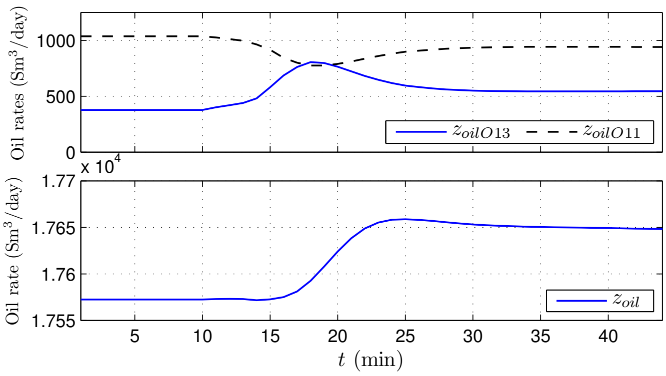

Fig. 3. Oil rates using unreachable setpoints.

By using an exact penalty function with penalty weight r, the pressure z_{pres1} never violates the upper constraint, meaning that the priority of optimizing oil production never exceeds the objective of keeping the process within its limits. With the change in choke openings shown in Figure 2, the corresponding changes in flow rates from the wells in Cluster O are shown in Figure 3, giving an increase in total oil production. Except from the limit on the inlet separator pressure, no other constraints are active. This solution would therefore be difficult to find without any form of optimization.

3.3 Using infeasible soft-constraints

The infeasible soft-constraints method is used to get a linear cost function representing the objective of maximizing total oil production as in (12), by choosing $z_{\mathrm{oil,min}}$ larger than the maximum oil production. Using $z_{\mathrm{oil,min}} = 208.3\,\mathrm{kg/s} = 20\ 000\,\mathrm{Sm^3/day}$, the same value as the infeasible setpoint in Section 2.4, the linear cost in (11) will be expressed as

$$-\sum_{i=1}^{P} r_{\mathrm{oil}} z_{\mathrm{oil},k+i}, \tag{15}$$

representing the objective of maximizing total oil production. As discussed in Section 2.4, the value of $z_{\mathrm{oil,min}}$ is not important as long as it is large enough to always be infeasible and not too large, possibly creating numerical problems. The penalty weights are chosen to be

$$r = \begin{bmatrix} r_{\mathrm{oil}} & r_{\mathrm{pres1}} & r_{\mathrm{presO}} \end{bmatrix}^\top = \begin{bmatrix} 1 & 10^3 & 10^3 \end{bmatrix}^\top$$

where optimizing total oil production is given a lower priority than operating within the constraints for the remaining CVs. Apart from choosing $z_{\mathrm{oil,min}}$, r and using $Q = \mathrm{diag}\{0,\, 0,\, 0\}$, the MPC setup is equal as in Section 3.2, giving the responses in Figures 4 and 5.

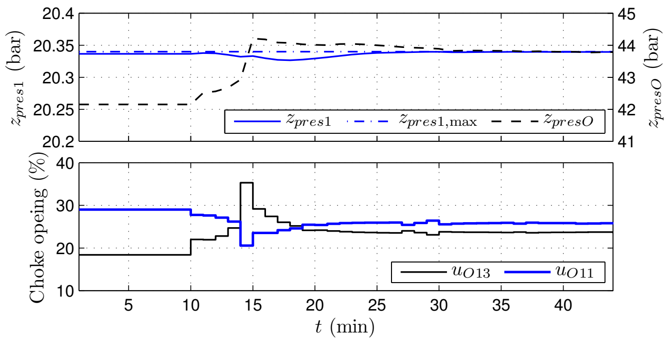

Fig. 4. Pressures and choke openings using infeasible soft-constraints.

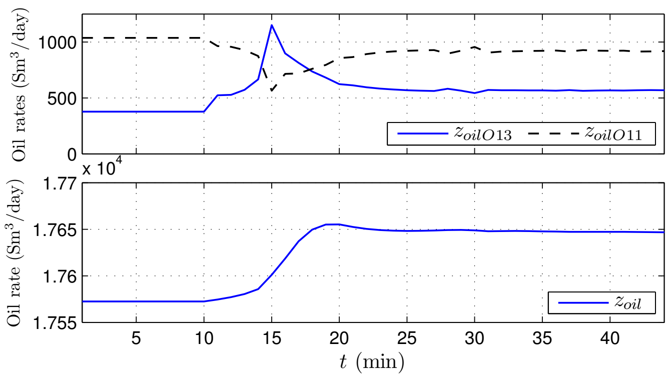

Fig. 5. Oil rates using infeasible soft-constraints.

These responses are similar to the responses obtained with the infeasible setpoints method in Section 3.2, giving approximately the same steady-state result. The controller seems to be somewhat more aggressive, which may be attributed to the use of a 'linear' cost compared to the 'quadratic' cost in Section 3.2. However, also aspects related to the implementation of the soft constraints in the SQP algorithm used may come into play here (cf. discussion at the end of Section 2.4).

4. DISCUSSION

In the two cases in Sections 3.2 and 3.3, the total oil production is increased with $71\,\mathrm{Sm^3/day}$ using unreachable setpoints and 73 Sm^3/day using infeasible soft-constraints, compared to the initial situation where the separator inlet pressure was on its maximum constraint. The increase in production is dependent on the choice of initial state that in this case was somewhat arbitrary, but in oil and gas production in general, even small increases in production rates can imply significant increased income – with an oil price of 75 USD per barrel, the increases reported above represent a yearly increased revenue of over 12 million USD.

Since the separator inlet pressure was at its constraint, the increase came from exploiting the different gas/oil relationships in the wells, see Figure 6, where the MGOR is the tangent line of the curves. Using (13), the maximum oil production from the two wells is achieved when the MGOR values are equal, giving parallel tangent lines in the points marked '+', where the total increase of oil production is 75 Sm^3/day. With the two methods used, almost equal MGOR values are found, where the gap is due to the flat optimum resulting from the tangent lines becoming almost parallel when approaching the optimum. Note that we have used the MGOR relationships to verify the solutions found, but these relationships are not included in the optimization problem in any form other than in the object of maximizing total oil production.

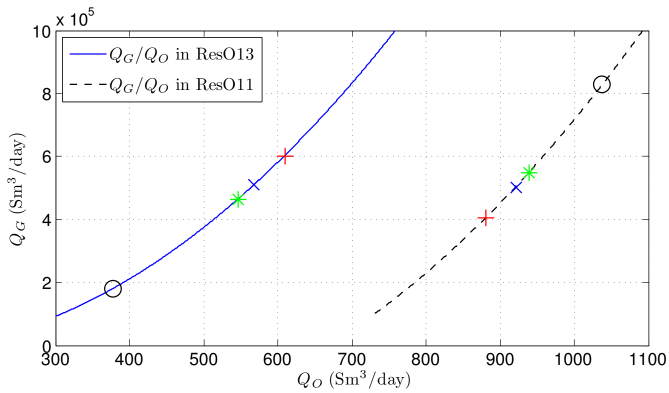

Fig. 6. $Q_{\text{gas}} - Q_{\text{oil}}$ relationships at the start ($\circ$) and end of the simulation, using unreachable setpoint ($*$) and infeasible soft-constraint ($\times$). The optimum is marked with '+'.

In this paper, we have concentrated on comparing two different one-layer approaches which can be implemented within standard NMPC software tools. A one-layer approach has several potential advantages (see also Section 2.2) compared to two-layer approaches, including that only a single model needs to be kept updated, disturbances can be counteracted as they appear, and economics can be optimized also during transients.

In Willersrud (2010), we have compared the unreachable setpoints and infeasible constraints-methods in a similar setup as in Sections 3.2 and 3.3, but where reservoir models with constant (but different) GOR curves were used. Results were similar to what was obtained herein, but in this case the optimum lay on some choke or process constraint, since equal MGOR cannot be achieved with constant GOR values in the wells.

REFERENCES

Awasthi, A., Sankaran, S., Nikolaou, M., Saputelli, L., and Mijares, G. (2008). Short-term Production Optimization by Automated Adaptive Modeling and Control. In *SPE Intelligent Energy Conference and Exhibition, Amsterdam, The Netherlands*. SPE 112239.

Backx, T., Bosgra, O., and Marquardt, W. (2000). Integration of model predictive control and optimization of processes. In *Proc. of IFAC Symposium on Advanced Control of Chemical Processes*, 249–260.

Bieker, H.P., Slupphaug, O., and Johansen, T.A. (2006). Real Time Production Optimization of Offshore Oil and Gas Production Systems: A Technology Survey. In *SPE Intelligent Energy Conference and Exhibition, Amsterdam, The Netherlands*. SPE 99446.

de Oliveira, N.M.C. and Biegler, L.T. (1994). Constraint handling and stability properties of model-predictive control. *AIChE Journal*, 40(7), 1138–1155.

Diehl, M., Amrit, R., and Rawlings, J.B. (2010). A Lyapunov function for economic optimizing model predictive control. *IEEE Transactions on Automatic Control*. Accepted.

Díez, M.D., Brusdal, K., Evensen, G., Barkve, T., and Mjaavatten, A. (2005). Opportunities and challenges of using sequential quadratic programming (SQP) for optimization of petroleum production networks. In *European symposium on computer aided process engineering*.

Engell, S. (2007). Feedback control for optimal process operation. *Journal of Process Control*, 17(3), 203–219.

Foss, B.A. and Schei, T.S. (2007). Putting nonlinear model predictive control into use. In *Assessment and Future Directions Nonlinear Model Predictive Control*, LNCIS 358, 407–417. Springer Verlag.

Kadam, J.V. and Marquardt, W. (2007). Integration of economical optimization and control for intentionally transient process operation. In *Assessment and Future Directions Nonlinear Model Predictive Control*, LNCIS 358, 419–434. Springer Verlag.

Rawlings, J.B. and Amrit, R. (2009). Optimizing process economic performance using model predictive control. In *Nonlinear Model Predictive Control*, 119–138. Springer Berlin.

Rawlings, J.B., Bonne, D., Jørgensen, J.B., Venkat, A.N., and Jørgensen, S.B. (2008). Unreachable setpoints in model predictive control. *IEEE Transactions on Automatic Control*, 53(9), 2209–2215.

Saputelli, L., Nikolaou, M., and Economides, M.J. (2006). Real-time reservoir management: A multiscale adaptive optimization and control approach. *Computational Geosciences*, 10(1), 61–96.

Scokaert, P.O.M. and Rawlings, J.B. (1999). Feasibility issues in model predictive control. *AIChE Journal*, 45(8), 1649–1659.

Seborg, D.E., Edgar, T.F., and Mellichamp, D.A. (2004). *Process Dynamics and Control*. Wiley & Sons, Inc.

Skogestad, S. (2004). Control structure design for complete chemical plants. *Computers & Chemical Engineering*, 28(1-2), 219–234.

Strand, S. and Sagli, J.R. (2004). MPC in Statoil – Advantages with in-house technology. In *Symposium on Advanced Control of Chemical Processes (ADCHEM), Hong Kong*, 97–103.

Urbanczyk, C.H. and Wattenbarger, R.A. (1994). Optimization of well rates under gas coning conditions. *SPE Advanced Technology Series*, 2(2), 61–68.

van Essen, G.M., van den Hof, P.M.J., and Jansen, J.D. (2009). Hierarchical Long-Term and Short-Term Production Optimization. In *SPE Annual Technical Conference and Exhibition, New Orleans, USA*. SPE 124332.

Willersrud, A. (2010). *Short-Term Production Optimization in an Offshore Oil and Gas Processing Plant Using Nonlinear Model Predictive Control*. Master's thesis, NTNU.

Würth, L., Rawlings, J.B., and Marquardt, W. (2009). Economic Dynamic Real-Time Optimization and Nonlinear Model-Predictive Control on Infinite Horizons. In *IFAC Symposium on Advanced Control of Chemical Processes*.