Coordinator MPC with focus on maximizing throughput

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Abstract

In cases where disturbances of economic importance have a dynamic character and if they occur frequently compared to the controlled plant responses, dynamic optimization is more suitable than traditional RTO. However, in many cases the optimal operation is the same as maximum plant throughput. To realize maximum throughput, the bottleneck(s) must be identified and maximum flow at the bottleneck must be implemented. In this paper we suggest to use a coordinator MPC with experimental step response models to maximize throughput. The local MPCs exploits its models and constraints to estimate the remaining feed capacity in each unit at each sample. The coordinator has then information from the local MPC with distance to the bottleneck and can manipulate on feeds and crossovers to maximize the throughput. The coordinator MPC has been tested on a dynamic simulator for parts of a gas processing plant and performs well for the simulated challenges.

Key words: bottleneck, maximize throughput, MPC

1 Introduction

Real-time optimization (RTO) offers a direct method of maximizing an economic objective function. Typically, RTO systems are model-based and part of a closed-loop process control system which objective is to maintain the process operation as close as possible to the optimum plant operation (Zhang and Forbes, 2000). When disturbances of economic importance have a dynamic character and especially if they occur frequently compared to the controlled

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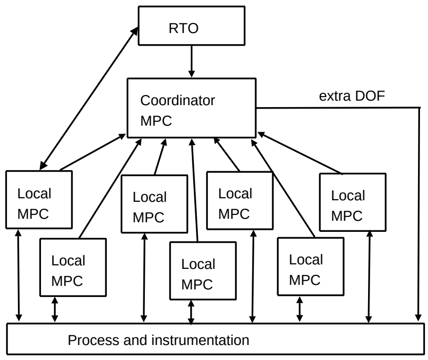

Fig. 1. The control hierarchy with the coordinator MPC

plant responses, steady state RTO will be inadequate to follow the optimal operation point in periods. In such cases dynamic RTO is more suitable, and different authors have discussed this subject, e.g. (Tosukhowong et al., 2004; Kadam et al., 2003)

In many cases the prices and market conditions are such that real-time optimization of the plant is the same as maximizing plant throughput. Optimize throughput in a current network is a common problem in several settings (Phillips et al., 1976; Ahuja et al., 1993). In this special but important case, optimal operation is the same as maintaining maximum flow through the bottleneck(s) of the plant (*max-flow min-cut theorem*). One solution to this problem is to use RTO and identify the bottleneck(s) based on a detailed steady-state model of the plant. However, the formulation of such a model is expensive and time consuming and the on-line solution is difficult. Actually, a nonlinear model is not necessary in this simple case because the objective is to identify the active "bottleneck" constraint. Therefore, a simpler solution is to use a "coordinator MPC" based on a linear model with constraints. The coordinator MPC task is to maximize an objective function and make decisions involving several local MPC applications, which typically handle product specifications and stability issues of smaller process units. As the name indicates, the coordinator MPC is placed on the top of the local MPCs in the control hierarchy and coordinates the underlying MPCs, as displayed in Figure 1. The coordinator MPC operates with feedback on minute's basis, compared to the typical RTO execution time of several hours. This leads to a faster correction of disturbances, model errors and transient dynamics.

The paper is organized as follows. Background information about inventory control and throughput manipulation are given in Section 2. Section 3 describes the optimization problem together with the extensions of local MPCs and description of the coordinator MPC. Section 4 illustrates a dynamic simulation case study and then a discussion follows in Section 5 before the paper is concluded in Section 6.

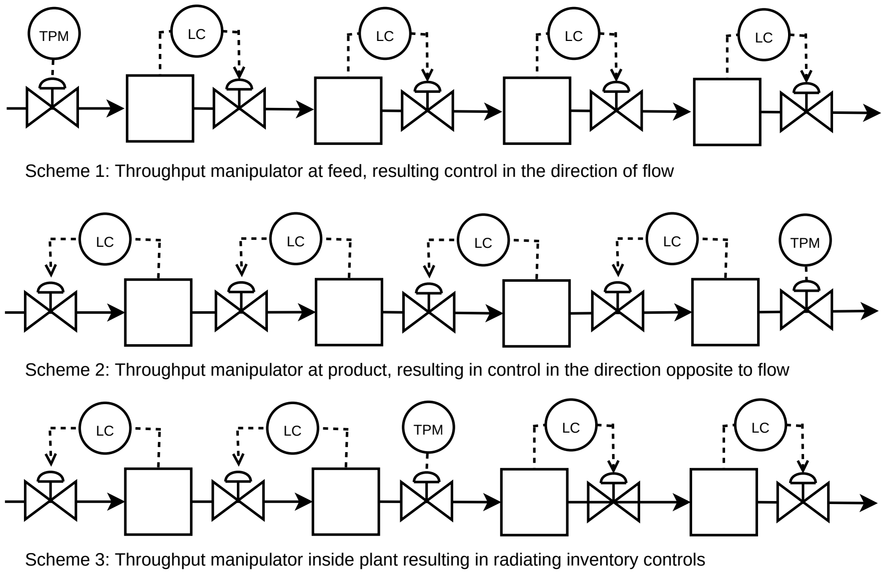

Fig. 2. Fundamental principles for inventory control, from Price et al. (1994)

2 Throughput manipulation

2.1 Inventory control

Inventory control deals with how the mass balance is maintained in the plant. A chemical plant has usually a single ”throughput manipulator” (TPM) which indirectly through the process and product requirements determine all the feed and product rates.

There are three basic schemes for inventory control (see Figure 2), depending on where in the process the TPM is located (Buckley, 1964; Price et al., 1994):

- *Scheme 1.* Feed as TPM (given feed): Inventory control system in the direction of flow (conventional approach)
- *Scheme 2.* Product as TPM (”on demand”): Inventory control system opposite to flow
- *Scheme 3.* TPM inside plant: Radiating inventory control

The selection of throughput manipulator is important, both for realizing optimal plant operation and for the final control system performance.

2.2 Modes of optimal operation

Most process plants have two main modes in terms of optimal operation:

Mode 1. Maximum efficiency, that is, minimize utility (energy) consumption with a given throughput. This mode of operation occurs when (a) the feed rate is given (or limited) or (b) the product rate is given (or limited, for example, by market conditions).

Mode 2. Maximum throughput. This mode of operation occurs when the product prices and market conditions are such that it is optimal to maximize throughput.

This paper focuses on mode 2. There is also a third, but less common mode:

Mode 3. Optimized throughput, that is, increase throughput until production cost for an extra unit equals price difference between product and feed. This mode of operation occurs when feed is available (feed rate is a degree of freedom), but prices are such that is not optimal to go all the way to maximum throughput.

Mathematically, optimal operation in all three cases is to minimize the cost J (maximize the profit $-J$), subject to satisfying given specifications and model equations ($f = 0$) and operational constraints ($g \leq 0$):

$$\begin{aligned} &\min_u \; J(x,u,d) \\ &\text{s. t. } f(x,u,d) = 0 \\ &\qquad g(x,u,d) \leq 0 \end{aligned} \tag{1}$$

Here u are the manipulated variables (including the feed rates), d the disturbances and x the (dependent) state variables. A typical profit function is

$$-J = \sum_i p_{P_i} \cdot Pi - \sum_i p_{F_i} \cdot F_i - \sum_i p_{Q_i} \cdot Q_i \tag{2}$$

where P_i are products, F_i are feeds,Q_i are utilities (heating, cooling, power), and p indicates the price for each of the element.

In terms of location of the TPM, scheme 1 (in Figure 2) is the natural choice for mode 1a (given feed), scheme 2 is the natural choice for mode 1b (given product), whereas scheme 3 is the best choice for modes 2 and 3 where the optimal throughput is determined by some conditions internally in the plant.

2.3 Maximum Throughput

In mode 2 the objective is to find a feasible solution with maximum throughput. In the general case with multiple (independent) feeds, the throughput may be defined as the sum of the weighted feeds, $F_w = \sum_i w_i F_i$. The maximum throughput is then the solution to the problem

$$\begin{aligned} \max_{u} \; & F_w \\ \text{s.t. } f &= 0 \\ g &\leq 0 \end{aligned} \tag{3}$$

For the case with a single feed this may be written on the form $J = -F$ in Equation (1) and we note that $dJ/dF = -1$ (also at the optimum). For multiple feeds, the simplest case are all the weights $w_i = 1$. More generally, w_i should express the relative value of processing the various feeds, but this value may be difficult to find. To find the maximum throughput for the case with multiple feeds, it may therefore be better to use the economic cost function in Equation (2).

In summary, we may solve the optimization problem in Equation (1) with J from Equation (2) in all three modes listed in Section 2.2.

- In mode 1, the feed rates F_i are given and the optimization problem is modified by adding a set of constraint, $F_i = F_{i0}$ (alternatively, the product rates could be given).
- In mode 2 (maximum throughput), the feed rates F_i are degrees of freedom, and the cost data are such that we have an constrained optimum with respect to the feed rates (i.e. $dJ/dF_i < 0$). Increasing F_i above its optimal (maximum) value gives infeasible operation.
- In mode 3 (optimized throughput), the feed rates F_i are degrees of freedom, and the cost data are such that we have a unconstrained optimum with respect to the feed rates (i.e. $dJ/dF_i = 0$). Increasing F_i above its optimal value is feasible, but gives a higher cost J.

Remark 1. Modes 2 and 3 are different modes of solutions to an identical optimization problem. In mode 3 we have a "trade-off" situation where the cost data are important for the solution. On the other hand, in mode 2 the cost data only determine (indirectly) the weighting of the feeds in the "throughput", and the cost date are usually much less important.

Remark 2. The maximum throughput (mode 2) is equal to the maximum value of the feed (F_0) for which the "maximum efficiency problem" (mode 1) is feasible.

Remark 3. Consider mode 2 with the cost $J = -F_w$. If we use a quadratic cost function, for example $J = (F_w - F_{ws})^2$ where F_{ws} is a high, unreachable set point for F_w, the solution is the same. This "trick" is used later solve the optimization problem by using a standard MPC solver with a quadratic objective function.

2.4 Bottleneck: Link between maximum throughput and TPM

We consider here maximum throughput (mode 2), and introduce the concept of "bottleneck" as a link between TPM and maximum throughput. Maximum throughput (maximum flow for the system) is defined as the solution to Equation (3) , and we have some additional definitions:

Definition 1. Maximum flow for a unit. The maximum flow (capacity) of a unit is the maximum feed rate that the unit can accept subject to achieving feasible operation. Mathematically, this corresponds to solving the maximum flow problem in Equation 3 for a given unit, that is, to find the maximum value of F_i that satisfies the constraints $f_i = 0$ and $g_i \leq 0$ for the unit.

Definition 2. Bottleneck (operation). A unit is a bottleneck if maximum throughput (maximum network flow for the system) is obtained by operating this unit at maximum flow (with no available capacity left).

Definition 3. Bottleneck constraints (operation). The active constraints at maximum flow in a bottleneck unit are called the bottleneck constraints. If one of the active constraints is a manipulated variable from a control point of view (usually a flow), then this is called a (direct) bottleneck manipulator.

Definition 4. Throughput manipulator (TPM). The throughput manipulator is the degree of freedom used to (indirectly) set the feed to the system. There may be more than one throughput manipulator for systems with more than one independent feed (the term independent here means that there is no (indirect) dependency between the feed rates due to system constraints).

Intuitively, the link between these concepts are as follows (e.g. Larsson et al. (2003); Skogestad (2004)): The maximum throughput in a plant (network) is limited by the "bottleneck" of the network. In order to maximize the throughput, the flow through the bottleneck should be at its maximum flow. In particular, if the actual flow at the bottleneck is not at its maximum at any given time, then this gives a loss in production which can never be recovered (sometimes referred to as a "lost opportunity"). To minimize the loss, the throughput manipulator (TPM) should be used to keep (control) the flow through the bottleneck as close as possible to its maximum.

These intuitive ideas are closely related to the problem of maximum flow in networks considered in the operations research community, (e.g. Phillips et al. (1976)). Such a network consists of sources, arcs, nodes and sinks. An arc is like a pipeline with given (maximum) capacity, and the nodes may be used to add or split streams. The main restriction is that the flow must satisfy conservation at the nodes. This may be written as a linear programming problem, and the trivial but important solution is that the maximum flow is dictated by the network bottleneck. To see this, one introduces "cuts" through the network, and the capacity of a cut is the sum of the capacity of the forward arcs that it cuts through. The *max-flow min-cut theorem* says that the maximum flow through the network is equal to the minimum capacity of all cuts (the minimal cut). We then reach the important insight that maximum network flow (maximum throughput) requires that all arcs in some cut have maximum flow, that is, they must all be bottlenecks (with no available capacity left).

In terms of process engineering systems, a unit with a single product is an arc, and flow splits and flow junctions are nodes. In network theory, the flow splits in nodes are free variables, like crossovers between parallel trains in "our" processes. A unit with several products (e.g. a distillation column) is a combination of an arc and a node, but there is usually a limited degree of freedom to adjust the split because of product constraints. To get a linear network the split factor must either be constant or a free variable.

To apply network theory to process engineering systems, we first need to obtain the capacity (maximum flow) of each unit (arc). This is quite straightforward, and involves solving a (nonlinear) feasibility problem for each unit. The capacity may also be computed on-line, for example, by using local MPC implementations as proposed in the next section.

Assumption: The mass flow through the network may be represented as a set of units (where each unit capacity is obtained locally) with linear flow connections.

Note that the nonlinearity of the equations within a unit is not a problem, but rather the possible nonlinearity in terms of flows between units. The main problem of applying linear network theory to process engineering systems is therefore that the flow split in a unit, e.g. a distillation column, is not constant, but depends on the state of its feed, and, in particular, of its feed composition. The main process unit to change composition is a reactor, so decisions in the reactor may strongly influence the flow in downstream units and recycles. Another important decision that affects composition, and thus flows, is the amount of recycle. The solution to this is probably to treat certain combinations of units, like a reactor-recycle system, as a single combined unit as seen from maximum throughput (bottleneck) point of view.

In summary, we have from the max-flow min-cut theorem the following useful insights (rules) about the maximum flow solution for a linear network which satisfies the assumption:

- *Rule 1.* At maximum throughput the network must have at least one bottleneck unit.
- *Rule 2.* Additional independent feeds and flows splits ("independent" means that they are not indirectly determined by other flows in the process, e.g. a crossover flow between processing trains) may give rise to additional bottle-

necks, and the idea of "minimal cut" may be used to identify the location of the corresponding bottleneck units.

The flow should be at maximum at the bottleneck. This has implications for control of the bottleneck unit (Rule 3), and in particular for use of the throughput manipulator (Rules 4 and 5).

- *Rule 3.* Focus on bottleneck unit. To maximize throughput, the flow through the bottleneck should be as close as possible to its maximum at any given time. This requires "tight" control of the bottleneck unit, as any deviation from optimal operation in the bottleneck unit due to poor control (including any deviation or "back off" from the bottleneck constraints) implies a loss in throughput (which can never be recovered).
- *Rule 4.* Use of TPM. Since the throughput is indirectly given by the maximum bottleneck flow, this requires that the TPM is used as a degree of freedom for control of the bottleneck unit. In practice, TPM is often used to control one of the bottleneck constraints (see Definition 3).
- *Rule 5.* Location of TPM. To further reduce the throughput loss due to imperfect control, TPM should be located so that controllability of the bottleneck unit is good. For example, if TPM is used to control one of the bottleneck constraints then the effective time delay from TPM to its bottleneck constraint should be small. Selecting TPM as a bottleneck manipulator (if there is one; see Definition 3) may be a good choice as it gives perfect control of this active constraint.
- *Rule 6.* Self-consistency of inventory control system. For material balance to be maintained, inventory control must be in the direction of flow downstream of TPM, and in direction opposite to flow upstream of TPM (see Figure 2)
- *Rule 7.* Back off at the bottleneck. To ensure feasibility dynamically, back off[2] is needed on the constraint variables in the presence of disturbances. Also, the requirement of stable operation may also prevent one from setting the flow at its maximum at the bottleneck. For example, in a reactor, cooling may be a bottleneck, but if cooling is used to stabilize the reactor temperature, then some back off from the maximum cooling rate may be required. Back off gives loss and therefore it is important to analyze which back off has the highest cost. Perfect control should be struggled for the loop with the most expensive back off.

The ideas of linear network theory may be very useful for "our" systems. Although the linearity assumptions will not hold exactly in most of "our" systems, the bottleneck result is nevertheless likely to be optimal in most cases.

[2] Back off is the deviation between set point and optimal value (constraint) which is primarily introduced to avoid infeasibility dynamically (Govatsmark and Skogestad, 2005)

3 Coordinator MPC for maximizing throughput

In terms of realizing maximum throughput there are two issues:

(1) Identify the bottleneck(s)
(2) Implement maximum flow at the bottleneck

In this paper, we propose a simple method for (indirectly) solving issue 1, by estimating and updating the remaining feed capacity in each unit (feedback solution). For simplicity, we consider conventional inventory control (scheme 1 in Figure 2) where the feed rate(s) is the TPM(s). We do not move the TPM to the bottleneck to solve issue 2 because of the bottleneck can move in operation. Instead we use MPC technology to manipulate on the TPM(s). If the bottleneck is an manipulated variable flow) we introduce a back off and leave its associated control loop in place.

To maximize the throughput, the objective is to identify the active *bottleneck* constraint(s). A *coordinator MPC* based on a linear model with constraints can be used in this case. Here there are two possibilities. The first is to use a coordinator MPC that duplicates all the models and constraints in the the local MPCs for each unit. However, duplication is undesirable; therefore, we suggest a more decoupled solution strategy. Since the location of the bottleneck(s) may change, it requires a measure of the remaining feed capacity (distance to the bottleneck) in each part of the plant.

3.1 Extension of the local MPCs

With MPC installed on each unit we may use this tool to obtain the remaining feed capacity for each unit. All the necessary models and constraints are available in the local MPC application and all that is needed is to solve an additional steady state optimization problem. In most cases the unit feed is a disturbance variable (DV) in the local MPC, if not, this must be added in the local MPC. The standard MPC solution at each time step consist of two parts (Seborg et al., 2003). First, a steady state solution to find feasible control targets (controlled variable (CV) set points and manipulated variable (MV) ideal values), and then a dynamic optimization. We suggest that the steady state part of the local MPC is extended to obtain an estimate of the remaining feed capacity in the unit

$$R_k = J_{k,max} - J_k \tag{4}$$

where J_k is the current throughput (sum of feeds) in unit k. The maximum feed rate $J_{k,max}$ may be found by solving a simple LP optimization, which is written as a minimization problem

$$
\begin{aligned}
\max_{x_k}\ J_k = \min_{x_k}\ f^T x_k, \quad \text{subject to} \\
b_{k,lower} \leq & A_k x_k \leq b_{k,upper} \\
0 \leq & x_k \leq x_{k,upper}
\end{aligned} \tag{5}
$$

where f and x_k are vectors in $\Re^n$, b_k is a vector in $\Re^m$, and A_k is an $m \times n$ matrix. To write the problem on this form, introduce first the vector X_k as all the MVs in the local MPC plus the feeds to the unit k, $F_1...F_l$,

$$
X_k = [MV_1\ ...\ MV_j\ F_1\ ...\ F_l]^T \tag{6}
$$

where j is the number of MVs and l is the number of feeds to the unit. To include the effects of past values for the MVs and the feeds, the end predicted value for MVs and CVs are used in the calculations instead of the current values. The LP formulation in (5) requires non-negative x_k, and we define therefore the vector x_k as

$$
x_k = X_k - X_{k,Low\ limit} \tag{7}
$$

The vector f weights the elements in x_k leading to J_k to become a sum of the unit feeds.

$$
f = [0\ ...\ 0\ \ -1\ ...\ \ -1] \tag{8}
$$

The A matrix contains the model gains between the inputs and the outputs in the local MPC and is given by

$$
A_k = \begin{bmatrix}
\Delta CV_{k,1}/\Delta X_{k,1}\ ...\ \Delta CV_{k,1}/\Delta X_{k,n} \\
\Delta CV_{k,2}/\Delta X_{k,1}\ ...\ \Delta CV_{k,2}/\Delta X_{k,n} \\
\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\
\Delta CV_{k,m}/\Delta X_{k,1}\ ...\ \Delta CV_{k,m}/\Delta X_{k,n}
\end{bmatrix} \tag{9}
$$

where m is the number of CVs and $n = j + l$.

The constraints in the LP problem are the same as in the steady state solver in the local MPC, with high and low limits on the CVs and MVs. The feeds in the LP problem is unbound upwards.

This leads to the following LP problem to be solved by the local MPC

$$
\begin{aligned}
\max_{x_k}\ J_k = \max_{x_k}\ F_k \quad \text{s. t.} \\
CV_{low\ limits} - A_k X_{k,low\ limit} \leq & A_k x_k \leq CV_{high\ limits} - A_k X_{k,low\ limit} \\
0 \leq & x_k \leq X_{k,high\ limits} - X_{k,low\ limits}
\end{aligned} \tag{10}
$$

The algorithm returns $J_{k,max}$ and remaining feed capacity, R_k can be found from Equation (4).

3.2 The throughput coordinator

Using the LP calculation of remaining feed capacity R_k in each local MPC, the problem becomes much more decoupled. The optimization at the coordinator level is to maximize the weighted overall feed rate within feasible operation and becomes:

$$\begin{aligned} \max_{MV} \ J = \max_{MV} \sum w_i F_i \quad & \text{subject to} \\ R_k \geq 0 & \\ R_k = G \cdot MV & \end{aligned} \tag{11}$$

where J is a weighted sum of the feed rates to the plant. The MVs at the coordinator level are typically the external feed rates and crossovers in the plant. G represents the model from each MV to R_k. Maximum flow rate can be realized with a standard MPC quadratic objective function by using a total plant feed as a CV with a high (not reachable) set point with lower priority than the capacity constraints. Other solutions are possible, but this set-up was found to work well in practice. The throughput coordinator is implemented using standard MPC software and the following cost function is used

$$\min_{MV} \left(\sum w_i F_i - F_{ws}\right)^2 + \sum \Delta MV^T Q \Delta MV \tag{12}$$

where F_{ws} is high unreachable set point for the weighted feed sum and Q is the penalty on MV moves.

In this case, experimental step-response models are used in the coordinator MPC. The model development may be demanding in practice due to long transport distances with several disturbances in the flow line that may occur during step-tests. However, for a given feed composition, it is possible to use simple mass balance to calculate the steady-state part of G. This gives a good estimate of the model gains.

The coordinator MPC should operate such that it is possible to keep each unit specification. However, unmeasured disturbances and slow responses may require some back off in the unit when the disturbances occur. The magnitude of the back off depends on the expected size of the disturbances and how strict the product specifications are. If the product is mixed on tanks before sale, violating the product specifications for a shorter period may be acceptable. The use of back off reduces the overall throughput (J), but makes the coordinator more robust to handle unmeasured disturbances.

The process dynamics seen by the coordinator MPC includes the local MPCs. Local MV saturation should be avoided so the local MPCs are more robust to handle disturbances and to linearize the process seen by the coordinator. To avoid local MV saturation, some back off on each MV in the local MPCs are included in the calculations of remaining feed capacity.

4 Kårstø gas processing case study

The Kårstø plant treats gas and condensate from central parts of the Norwegian continental shelf. The products are dry gas, which is exported through pipelines, while natural gas liquids (NGL) and condensate are exported by ships. The Kårstø plant plays a key role in the pipeline structure in the Norwegian Sea and therefore the plant throughput is very important. Also, from a Kårstø point of view, the plant has relative low feed and energy costs and high product prices, which leaves the throughput as the most important variable for the economy. There are no recycles in the plant. The feed is also in most cases available and can be used as a free variable within some ranges. With these assumptions, the economic objective function for the plant can be simplified to maximize throughput. The feed enters the plant from three different pipelines and the feed composition may change frequently in all three lines. Changes in feed compositions can move the main bottleneck from one unit to another and affect the plant throughput. This argues for a DRTO application to optimize the plant operation. However, with the simple objective function structure and a simplified process model, a coordinator MPC can be used as a DRTO to handle transient dynamics and faster disturbances.

The coordinator MPC approach has been tested with good results using the Kårstø Whole Plant simulator. This is a dynamic simulator built in the software D-SPICE®.

4.1 The case

To demonstrate the applicability of the coordinator MPC, we use a detailed simulation model of parts of the Kårstø plant. To avoid the need for large computer resources, only parts of the whole plant are used in the case study. The selected parts consist of two fractionation trains, T-100 and T-300, both have a deethanizer, depropanizer, debutanizer and a butane splitter. In addition T-300 has two stabilizers in parallel. The simulated parts of the plant are shown in Figure 3. There are two separate train feeds, a liquid stream from a dew point control unit (DPCU) that is divided between the two trains, and a crossover. The five streams are MVs in the coordinator MPC and indicated

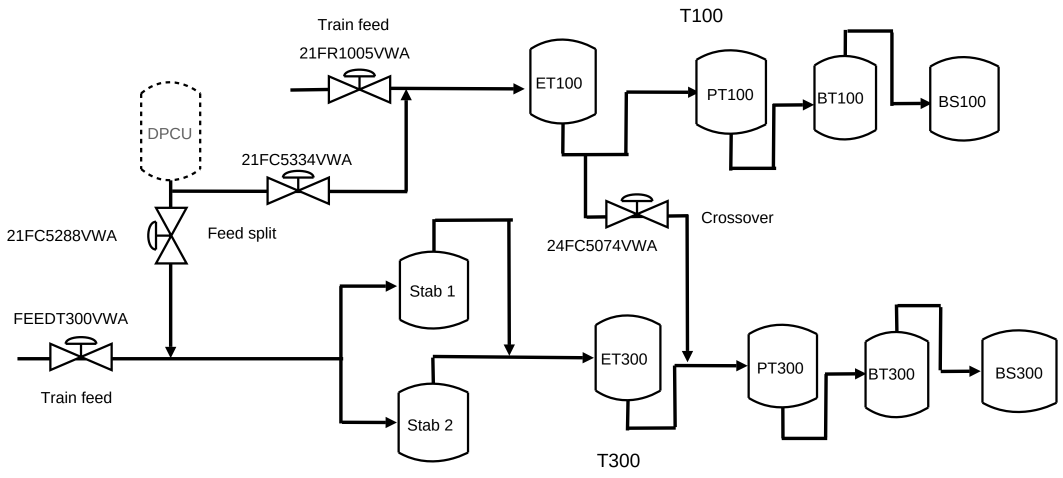

Fig. 3. The simulated parts of the Kårstø plant

by valves in Figure 3.

The local MPCs and the coordinator are implemented in Statoils SEPTIC [3] MPC software (Strand and Sagli, 2003). Data exchange between the simulator and the MPC applications is done by the built-in D-SPICE® OPC server.

4.2 Implementation of the local MPCs

The main control objective for each column is to control the quality in the top and bottom streams, by manipulating boil-up and reflux flow. In addition, the column must be kept under surveillance to avoid overloading, which is an important issue when maximizing throughput. Differential pressure is a good indicator of flooding, according to Kister (1990). Also the remaining feed capacity for each column (see Equation (4)) is calculated in the local MPC.

Limitations in the basic control layer and in the process equipment must be considered. The product qualities are described as impurity of the key component and a logarithmic transformation is used to linearize over the operating region (Skogestad, 1997).

In general, the local MPCs are configured as followed:

- CV: Impurity of heavy key component
- CV: Impurity of light key component
- CV: Column differential pressure
- MV: Reflux flow rate set point

[3] Statoil Estimation and Prediction Tool for Identification and Control

- MV: Tray temperature set point in lower section
- DV: Column feed flow

Some of the columns have other limitations in addition to the list above due to their design and these are included as CVs in the local MPC. The CV and MV limits must be given reasonable values, especially since the limits are included in the remaining feed capacity calculation, see Equation 10. The high limits on the product qualities are given by the maximum levels of impurity in the sales specifications and the differential pressure high limit is placed just below the flooding point.

The CV prioritizing for the local MPC is as follows:

(1) High limit differential pressure
(2) Quality limits
(3) Quality set points

where 1 has the highest priority. The priority list is used in the steady state part in the MPC solver and leads to relaxation of the quality set points/limits when the application predicts on the differential pressure high limit. By relaxation the feed rate can be maintained without flooding the column.

The relationship between the inputs and outputs is expressed with experimental step-response models. The models are generated by executing step-tests in the simulator and the responses are recorded in the SEPTIC MPC software. The sample time in the local MPC is set to 1 minute. From experience this is sufficiently fast for the distillation column dynamics and is the actual sample time used in the plant today.

Several tuning parameters must be chosen to obtain a rational use of the MVs to reach the control targets. The most important tuning parameters are listed in Aske et al. (2005). The tuning is mainly based on the running applications at the plant where this exists. For the columns that currently do not have MPC installed at the plant, the MPC is tuned in the same manners.

4.3 The design and implementation of the coordinator MPC

With the local MPCs in place, the coordinator MPC can be set up. The inputs and the outputs of the coordinator MPC are as follows:

- CV: Total plant feed (PLANT FEED)
- CVs: Remaining feed capacity in each column, 10 in total (ET100, PT100, BT100, BS100, STAB1, STAB2, ET300, PT300, BT300, BS300)
- CV: T-100 deethanizer sump level controller output (LC OUTLET)

- MV: Train feed flow T-100 (21FR1005VWA)
- MV: Train feed flow T-300 (FEEDT300VWA)
- MV: Feed flow from DPCU to T-100 (21FC5334VWA)
- MV: Feed flow from DPCU to T-300 (21FC5288VWA)
- MV: Crossover flow from T-100 to T-300 (24FC5074VWA)

The total plant feed is here defined as the sum of the train feeds and the flows from the DPCU. The level controller output as a CV follows to avoid emptying or filling up the sump level in the deethanizer T-100 when manipulating the crossover. The remaining feed capacity low limits, and high and low limits of the level controller output have high priority whereas the total plant feed has a high, not reachable, set point with lower priority.

Range changes in the local MPC, like MV and CV limits changes, have a direct influence on the remaining feed capacity measure and must also be handled by feedback with the current coordinator design. Nonlinear effects in the process causes modeling error in the coordinator and must also be handled by feedback. All these effects argue for a fast feedback sampling in the coordinator MPC. The coordinator execution rate is slower than in the local MPCs to ensure robustness in the feedback loop and is here chosen to be 3 minutes.

The column capacity depends both on the column feed flow and the feed composition. At the Kårstø plant, only the feed flow is manipulative. Due to the deadtime in the GC measure in the plant today, the feed composition changes are characterized as unmeasured disturbances in the simulations and must be handled by feedback. The coordinator models are experimental step-response models, and are found in the same way as in the local MPCs. The models were obtained at 80-95% of the maximum throughput which is typical flow rates in the plant today.

Tuning of the coordinator MPC is a trade-off between MV (feed) variation and CV constraint violation. Some constraint violation cannot be avoided due to the process response times, unmeasured disturbances and model errors. The tuning should not be so aggressive that model errors are amplified, which means that some constraints back off will be necessary. The low limit in the remaining feed capacity CVs represents back off and is based on 1-2% of the maximum column feed. Feed composition disturbances will have the largest impact on the first columns, these column needs larger back off than the following columns.

4.4 Results from the simulator case study

The performance to the coordinator MPC is illustrated with three different cases:

(1) Move the plant from an unconstrained operation to maximum throughput (at $t = 0$ min)
(2) Change in feed composition (at $t = 360$ min)
(3) Change in a CV limit in a local MPC (at $t = 600$ min)

All three cases are common events at the Kårstø plant and therefore used here in the simulator example. Feed composition changes are the most frequent disturbance that affect maximum throughput. The coordinator should also handle operator changes in the local MPCs as illustrated by changing a CV high limit.

4.4.1 Case 1: Move the plant to maximum throughput

In this case the plant is not operated at maximum throughput, and the coordinator is turned on to move the plant operation from a non-optimal to an optimal operation point.

The CVs in the coordinator MPC are displayed in Figure 4 whereas the MVs are shown in Figure 5. The vertical lines in the plots are the time where disturbances are introduced (Case 2 and 3). From Figure 4, the deeethanizer in T-100 (ET100) and the stabilizers (Stab1 and Stab2) are bottlenecks in their flow lines. Also the butane splitter in T-300 (BS300) reaches its capacity limit in the beginning due to some feed flow disturbances from the upstream column. However, there is available capacity in the depropanizer and the downstream columns in T-100 and the coordinator uses the crossover (see 24FC5074VWA in Figure 5) to reroute and unload the T-300 butane splitter.

Looking into a local MPC, like the butane splitter in T-100 displayed in Figure 6, the MPC relax on the quality set points because the column reaches the differential pressure high limit. This is due to the priority hierarchy in the local MPC, as mentioned in Section 4.2.

4.4.2 Case 2: Change in feed composition

A momentary feed composition change is introduced to the T-100 feed, which is the sum of 21FR1005VWA and 21FC5335VWA. The composition change is given in Table 1 and occurs at time $t = 360$ minutes, at the first vertical line in Figures 4, 5 and 6. The ethane reduction leads to an increase in the

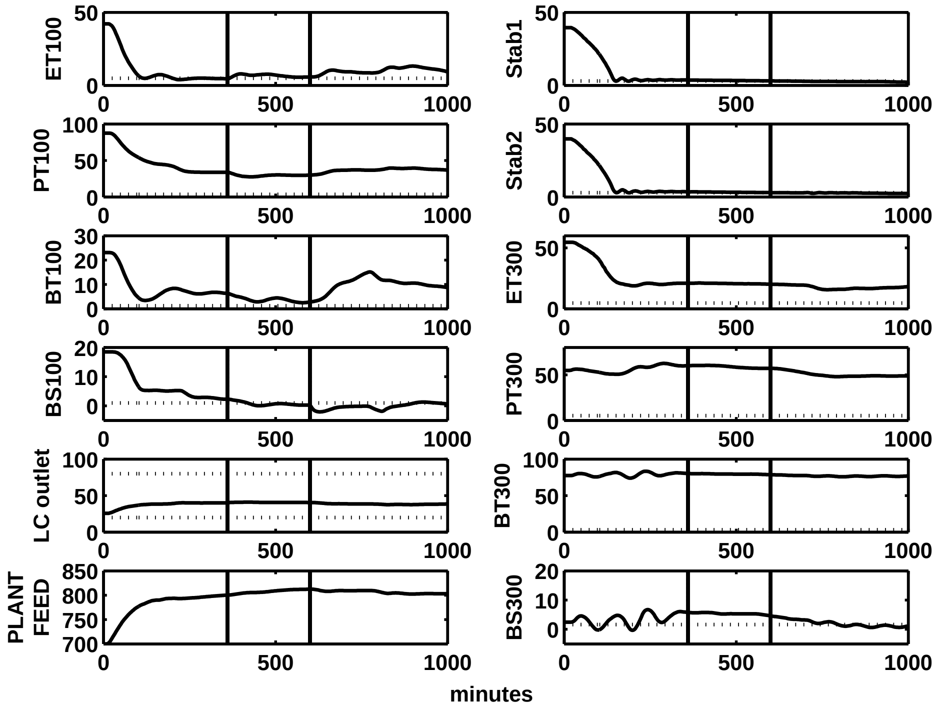

Fig. 4. CVs in the coordinator MPC, remaining feed capacity and plant feed in t/h, LC outlet in %. Vertical lines indicate new case.

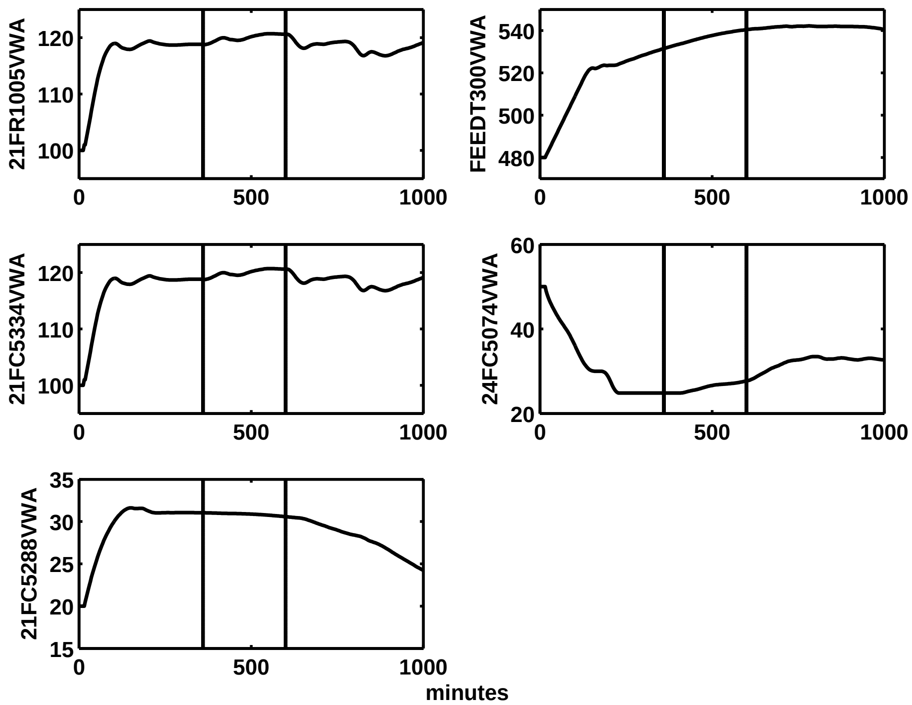

Fig. 5. MVs in the coordinator MPC, flows in t/h. Vertical lines indicate new case.

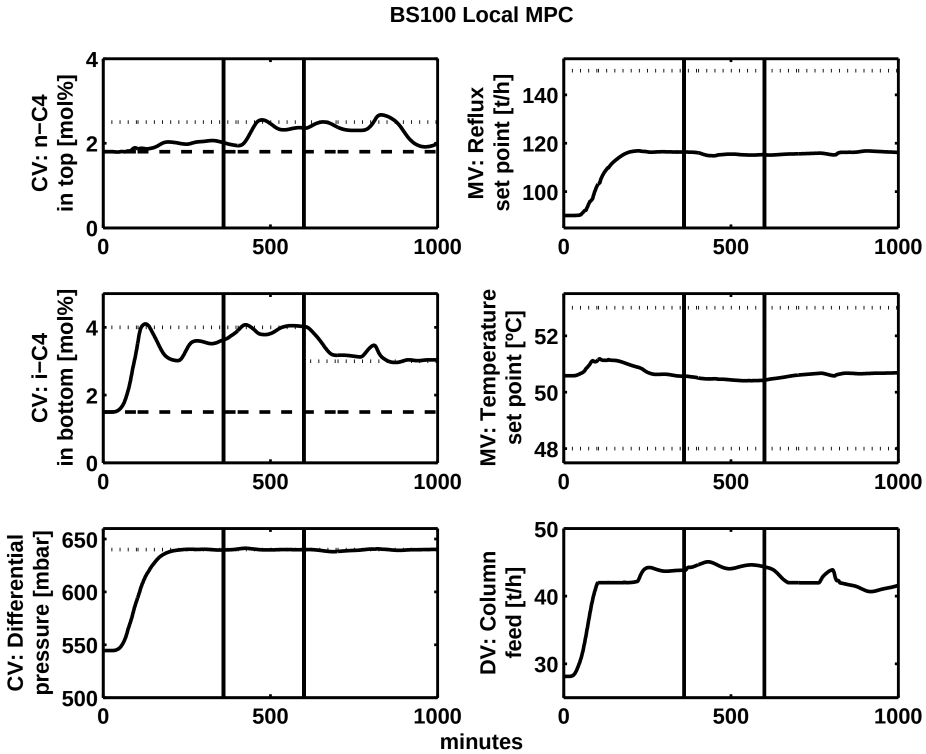

Fig. 6. CVs, MVs and DV to the butane splitter in T-100. Vertical lines indicate new case.

Component	% nominal change	% point change
Ethane	-3	-1.1
Propane	2	0.71
Iso-butane	10	0.56
N-butane	-3	-0.34
Iso-pentane	5	0.09
N-pentane	5	0.10

Table 1
Feed composition change in the T100 feed at $t = 360$ minutes

remaining feed capacity in T-100 deethanizer (ET100) and makes it possible for the coordinator to increase the train feed. However, the increase in iso-butane content reduces the remaining feed capacity in the butane splitter (BS100). There is remaining feed capacity in depropanizer in T-300 and the downstream columns so the coordinator uses the crossover to keep the butane splitter in T-100 within its capacity. The butane splitter in T-100 becomes a bottleneck, together with the deethanizer in T-100 and the stabilizers in T-300.

4.4.3 Case 3: Change in a CV limit in a local MPC

With the butane splitter in T-100 (BS100) operating at its capacity limit, the operator reduces the bottom quality high limit in the local MPC, as can be seen at $t = 600$ minutes in Figure 6. This leads to a reduction in the calculated remaining feed capacity which is not predicted by the coordinator MPC and the feed flow must then be adjusted by feedback. The coordinator increases the crossover since there is some available capacity in the T-300 string, but must also reduce the T-100 in addition. Now both the butane splitters (BS100 and BS300) are bottlenecks in the plant, together with the stabilizers (Stab1 and Stab2) whereas the deethanizer in T-100 is not a bottleneck any more. This last case illustrates bottlenecks movements in the simulator.

5 Discussion

In many cases the plant economy can be simplified to maximum throughput. If the flows between the units can be linearized, coordinator MPC is well suited for such cases. By using a decoupled strategy based on remaining feed capacity in each unit, the coordinator MPC exploits the already existing control structure from the local MPCs. This leads to a much smaller modelling effort compare to other optimization tools like RTO, but can still give a large part of the earnings. The computation time in a coordinator MPC is also small, and gives the opportunity to fast execution and faster corrections of disturbances, model errors and transient dynamics. The coordinator works as a DRTO and ensures the dynamic transfer for the steady state optimum.

If RTO is implemented on the plant, it can be combined with the coordinator MPC, as illustrated in Figure 1. Some of the calculated set points from the RTO are in that case sent to the coordinator MPC instead of the local MPC. The coordinator MPC controls then the dynamic transfer to the steady-state optimum to ensure that it is feasible.

It is possible to avoid the coordinator MPC layer by gathering all the local MPCs in one large application. However, for a complete plant the application will be over-complex leading to challenging modelling and maintenance. Introducing an extra layer in the hierarchy with smart decomposition reduces this complexity. Also, the local MPCs and the coordinator MPC have different tasks and are more easy-to-follow for operators.

The back off is necessary in the coordinator due to unmeasured disturbances and the long process response times, and should be selected according to the controller performance and the acceptable constraints violations. However, by including more plant information in feed forward control, the back off can be reduced and a higher throughput can be achieved. In this case study the feed composition changes have the largest impact on the throughput and should be included in some manner in the coordinator MPC.

The coordinator MPC uses linear models while the process is nonlinear. In cases where the nonlinearities mostly are reflected in model gains, gain scheduling of the model improve the performance. Gain scheduling is possible to include in the current model form. None of the models in the simulated case have gain scheduling, but for some models describing valve outlets, gain scheduling will probably give better prediction. With significantly nonlinearities, other model types in the coordinator MPC should be evaluated.

Due to the lack of fast and explicit feed composition measurements in the plant, feed composition changes are treated as unmeasured disturbances in the simulations in the current concept. However, the concept can be extended by using intermediate flow measurements as indicator for feed composition changes. Therefore, the use of alternative model structures that will simplify and propagate model corrections from intermediate flow measurements should be evaluated.

The dynamic performance to the coordinator MPC can be improved by using buffer volumes in the plant. By manipulating on the buffer volumes, the flow rate through a bottleneck can be corrected faster due to shorter dead time and settling time in the plant, compare to using only the feed valve(s). In this simulated case the buffer volumes are limited, however, in cases with larger buffer volumes this should be considered. Other linking variables between the units can also be considered, like decreasing impurity in an upstream column product to decrease the load to the downstream unit.

Maximum throughput as the objective function is a special case. If the feed turns to be limited for a period, the economic optimum will be different since energy costs and product prices should then be included in the objective function. In such a case the coordinator will not lead to optimal plant operation.

6 Conclusion

In many cases, optimal operation is the same as maximizing throughput. In this paper we suggest to use a coordinator MPC with experimental step response models to be used as a DRTO to maximize throughput. Realizing maximum throughput, the issues of identify bottleneck(s) and implementing maximum flow at the bottleneck(s) are important. The first issue is solved by using the models and constraints from the MPC applications around units to obtain an estimate of the remaining feed capacity at each sample. Maximum flow at bottleneck(s) can be implemented using throughput manipulators. However, the bottlenecks may move in the plant and that requires redesign of the throughput manipulators and the inventory control system. We therefore design a coordinator MPC to manipulate on plant feeds and crossovers. The coordinator MPC has been tested on a dynamic simulator for parts of a gas processing plant. The coordinator MPC performs well for the simulated challenges.

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