Industrial Implementation of a Coordinator MPC for Maximizing Throughput at a Large-Scale Gas Plant

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Abstract: An industrial implementation of a coordinator MPC to maximize throughput at the large-scale Kårstø gas plant is described. The "coordinator MPC" coordinates the flows through the network and not the local MPCs. It uses as degrees of freedom (MVs) the flows not used by the local MPCs (feeds, crossovers), and maximizes the throughput subject to the keeping the remaining capacities in all units zero or positive. A key idea is to use the local MPCs to estimate the remaining capacities in the units (Aske et al., 2008). Although not fully implemented, the coordinator MPC is found to be a promising tool for implementing maximum throughput.

Keywords: Model based control, throughput, implementation, optimization, capacity.

1. INTRODUCTION

This paper describes an actual industrial implementation of the method for maximum throughput proposed earlier by Aske et al. (2008). The application is the Kårstø gas processing plant located in Norway, which receives rich gas and unstabilized condensate through pipelines from more than 30 producing offshore fields. This set high demands, not only to the plant efficiency and its regularity, but also to the plant throughput. Limited gas plant processing capacity means that one or more fields must reduce production or even shut down. Therefore, it is important that the Kårstø plant does not become a "bottleneck" in the Norwegian gas transport system. The Kårstø plant has no recycles or reactors, but it has several independent feeds and parallel flows that make it possible to have multiple bottlenecks at the same time. The bottlenecks may move due to disturbances, thus the throughput maximizing is a dynamic and multivariable problem.

The overall feed rate (or more generally the throughput) affects all units in the plant. For this reason, the throughput is usually not used as a degree of freedom for control of any individual unit, but is instead left as an "unused" degree of freedom (u^c) to be set at the plant-wide level. The throughput at the Kårstø plant is presently set by the operators who manipulate the feed valves to satisfy orders from the gas transport system (operated by another company). The objective of this work is to coordinate the throughput manipulators (u^c) to achieve economic optimal operation.

In general, to optimize the economic operation of a plant, one may use real-time optimization (RTO), normally based on (rigorous) steady-state models. Standard RTO methods require the plant to be close to steady state before performing a reoptimization based on data reconciliation or parameter estimation (Marlin and Hrymak, 1997). However, many plants are rarely at steady state or important economic disturbances occur more frequent than the controlled plant response times. At least in theory, it is then more suitable to use dynamic optimization with a non-linear model, which may be realized using dynamic RTO (DRTO) or non-linear model predictive controller (MPC) with an economic objective, e.g. Engell (2007); Strand (1991).

In this study, a different approach is used. We assume that optimal economic operation is the same as maximizing plant throughput, subject to achieving feasible operation (satisfying operational constraints in all units) with the available feeds. This corresponds to a constrained operation mode with maximum flow through the bottleneck(s). At maximum throughput, all throughput manipulators (u^c) are used to satisfy active constraints (bottleneck). Thus a nonlinear model of the entire plant is not needed, and instead linear MPC may be used. One option is to combine all the MPCs in the plant into a single application. However, here we choose to decompose the problem by keeping the local MPC applications and introducing a coordinator MPC (Aske et al., 2008) to maximize throughput. The coordinator uses the remaining degrees of freedom (u^c) to maximize the flow through the network subject to satisfying given constraints. The remaining degrees of freedom (u^c) include feed rates, feed splits and crossovers. The constraints are the feasible remaining capacities of the individual units ($R_k > 0$). The feasible remaining capacity R_k is how much more feed unit k can receive while operating within its constraints. For most units, R_k is not a quantity that can be measured, because it depends on the operation of the unit. For

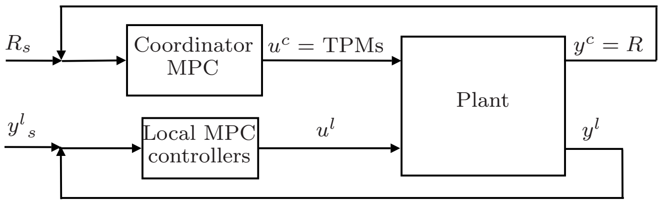

Fig. 1. Plant decomposition by coordinator MPC. The local MPC applications uses u^l to control the local targets y^l_s, whereas the coordinator uses the throughput manipulators (u^c = TPMs) to control the remaining capacity ($y^c = R$) in the units.

example, the capacity may be increased by producing less pure products. A key idea in the approach of Aske et al. (2008) is to use the local MPC to estimate R_k. By estimating R_k for each unit, the plant-wide control problem is decomposed and the application becomes smaller in size and hence easier to understand and maintain. The plant decomposition is illustrated in Fig. 1.

This paper considers about half of the Kårstø gas processing plant. The application presently includes 12 distillation columns, 2 compressor stages, 4 feed valves and 2 crossovers (splits). The main reason for not including the entire plant is that local MPC applications are yet not implemented on all units. All MPC applications at the Kårstø plant use the in-house SEPTIC technology (Strand and Sagli, 2003).

This paper is organized as follows. The local MPC controllers for the individual units are discussed briefly in Section 2. The local MPCs adjust the local degrees of freedom (u^l) such that the operation is locally feasible. However, local feasibility requires that the feed rate to the unit F^l_k is below its maximum capacity, $F^l_{k,max}$, and one of the tasks of the plant-wide coordinator is to make sure that this is satisfied. The maximum capacity for a unit ($F^l_{k,max}$) may change depending on disturbances (e.g. feed composition) and needs to be updated continuously. To estimate $F^l_{k,max}$ by using the already existing models in the local MPCs is discussed in Section 3. Section 4 discusses the coordinator MPC, including control design choices, model development, tuning issues and test runs. Experience from the implementation at the Kårstø site is summarized in Section 5. An extended version of this paper is found in Aske (2009, Ch. 6)

2. LOCAL MPC APPLICATIONS

Presently, all the local MPC applications for the coordinator are on two-product distillation columns. The main control objective for each distillation column is to control the quality of the distillate- (D) and bottoms (B) products. In addition, the column must be kept under surveillance to avoid overloading, where column differential pressure (Δp) is used as an indicator.

The local MPCs are configured with the following controlled variables (CVs), manipulated variables (MVs) and disturbance variables (DVs):

CV (set point + max constraint): Impurity of heavy key component in D.
CV (set point + max constraint): Impurity of light key component in B.
CV (max constraint): Column differential pressure (Δp).
MV: Reflux flow rate set point (L).
MV: Tray temperature set point (T_s).
DV: Column feed flow.

These MVs correspond to the local degrees of freedom (u^l) and the CVs correspond to the local outputs (y^l), see Fig. 1. Some of the columns have additional variables, but in principle, all the columns have the same control configuration.

The local MPC problems are solved at each sample time using a standard two-step approach, where first a steady-state problem is solved with constraint relaxation until the predicted final steady state is feasible, and then the "standard" dynamic MPC problem is solved with the possibly recalculated (reachable) set points and constraints. The high limit differential pressure has the highest priority, followed by impurity limits and then impurity set points. This priority hierarchy may leads to a relaxation of the impurity set points (and in worst case the limits) to avoid exceeding the differential pressure high limit. By using relaxation, the column can handle the given feed rate without flooding the column, but note that the exceeding the limits may result in an unsellable product. In the dynamic optimization part, constraints are handled by adding penalty terms to the objective function.

The local MPC applications are based on experimental step response models. The prediction horizon is 3 to 6 hours and the sample time is 1 minute.

3. ESTIMATE OF REMAINING CAPACITY

In this section, the procedure used by the local MPCs for estimating the remaining capacity in each unit (R_k) is explained.

The remaining capacity for unit k is the difference between the current feed F^l_k and the feasible maximum feed $F^l_{k,max}$

$$R_k = F^l_{k,max} - F^l_k \tag{1}$$

The feed to the local unit F^l_k is assumed to be a DV in the local MPC application. The maximum feed to the unit k is then easily obtained by solving an additional steady-state LP-problem subject to the present initial state, linear model equations and constraints used in the local MPC. $F^l_{k,max}$ is calculated using the end predictions (steady-state model) for the variables. This to include both past MV moves, disturbances and future MV moves for the local MPC. This indirectly assumes that the closed-loop response time for the local MPC is faster than for the coordinator. Note that $F^l_{k,max}$ can change due to updated measurements, disturbances (e.g. feed compositions changes), changes in the constraints and model changes in the local MPCs. The current feed to the unit (F^l_k) is measured, either by a flow transmitter or by a level controller output (valve opening) if a flow transmitter is not available.

The accuracy of the estimated remaining capacity depends on:

- The validity of the models used in the local application. The algorithm uses the end prediction and therefore the steady-state gain is in particular important.
- The appropriate use of gain scheduling for CV-MV pairs with larger nonlinearities. Here “gain scheduling” means that the model gain is updated (scaled) based on the current operation point.
- The CV constraints must reflect the true operational limits and the MV constraints must be reasonable.

Let us explain the first two points in more detail. An incorrect steady-state gain leads to a poor estimate of the remaining capacity and because the coordinator MPC has slow dynamics, it will take a long time before the feedback can correct for the error. A too high remaining capacity estimate lead to a oscillating behavior because of the long delays in the flow network. Another issue is that the operators will not trust the remaining capacity estimates if the estimates are far away compared to their own experience.

The remaining capacity estimate uses the CV constraints and not the CV set points. For a distillation column this implies that the distillate and bottoms quality constraints are used instead of the CV set points because set point deviations are acceptable if the alternative is feed reduction. This leads to an estimated capacity that is often larger than expected by the operators.

For units with several feeds, the LP optimization will maximize the feed with the smallest steady-state gain (smallest predicted effect on capacity), whereas the other feeds will go to zero. However, some feeds cannot be set to zero, because they are outlet from an upstream unit with no possibility for routing it elsewhere. In this case, the LP optimization is set to maximize the feed from the flow line the unit must process and the other feeds are held constant in the optimization.

Compressors are also included in the application, but at present there are no MPC applications implemented on these. To estimate the remaining capacity of the compressors one option could be to consider the percent load (given by the speed). However, it may not always be possible to reach 100% load due to other constraints, for instance the turbine exhaust gas temperature. To consider several constraints, we therefore use MPC applications with no control tasks, but with only CVs and DVs and the models between them to estimate the remaining capacity. A copressor stage consists of several copressors, but local control handles the distribution between parallel compressors (equal distance to the compressor control line), therefore is only one remaining capacity needed at each compressor stage.

At present, the estimates are based on experimental models. However, rigorous models for local units can also be used to predict the remaining capacity. This is attractive for units where experimental modelling is difficult, for example, due to nonlinearities. This illustrates the flexibility with this decomposition where the best available model can be used to predict the remaining capacity.

4. COORDINATOR MPC

4.1 Objective, variables and constraints

The Kårstø plant is shown in Fig. 2 where most of the CVs, MVs and DVs for the coordinator MPC are indicated. The coordinator MPC maximizes sum of the total plant feed which is the sum of the feeds to train 100 (T100), train 200 (T200), train 300 (T300), train 400 (T400) and the dew point control unit (DPCU). The application consists of:

- 6 MVs: 4 feed rates, 1 crossover, 1 feed split.
- 22 CVs: Remaining capacity of 12 distillation columns and 2 compressors stages, 7 other constraints plus the main objective: total plant feed with a high, unreachable set point with lower priority.
- 7 DVs: 3 feed rates, 2 feed compositions, 1 crossover, 1 feed split.

The “other” 7 CV constraints are related to the use of MVs, that is, levels constraints to avoid filling or emptying of buffer tanks and sump volumes, pressure constraints in the pipelines and pressure controller outputs. The CV “total plant feed” is the sum of the plant feeds and is given by

$$\begin{aligned}\mathrm{TOTALFEED} &= \mathrm{20FC1001A} + \mathrm{20FC2001A} + \mathrm{27FC3108} \\ &+ \mathrm{27FC3208} + \mathrm{21FC4125A} + \mathrm{21FC4225A} + \mathrm{21FC5219}\end{aligned} \tag{2}$$

where the variables are marked in Fig. 2. In general, the feeds could have different weighting, but at present, their weights are equal. Of the 22 CVs, only the total plant feed is set point controlled; the other CVs are constraints.

The MVs (throughput manipulators) are the feed rates, a crossover between parallel trains (from T100 to T300) and a feed split to T300. Other throughput manipulators that affect the CVs in the sub-application are included as DVs. Later, if the coordinator MPC is extended to the whole plant, most of these DVs will become MVs. The feed compositions (DVs) reflects the gas/liquid split, and determine the split between gas flow to the compressors and liquid flow to the fractionation and are estimated from flow- and temperature measurements.

The objective function in the SEPTIC MPC algorithm is quadratic, while the objective function for the the maximum throughput problem is linear. To obtain a quadratic objective function that fits directly into our quadratic MPC algorithm, we have used the common trick of introducing a quadratic set point deviation term with a high and unreachable set point with a lower priority than the capacity constraints. (Of course, the actual case function used by the coordinator MPC has additional terms and weights). The first step of the coordinator MPC solution will then result in a recalculated (reachable) set point for the total feed.

Each variable (CV, MV and DV) belongs to one or more sub-groups that will be deactivated if one critical variable in the sub-group is deactivated. For instance, if a local MPC application is turned off, the corresponding remaining capacity CV is deactivated, and this critical variable suspends the whole sub-group. By using this condition-based logic, the coordinator MPC can operate

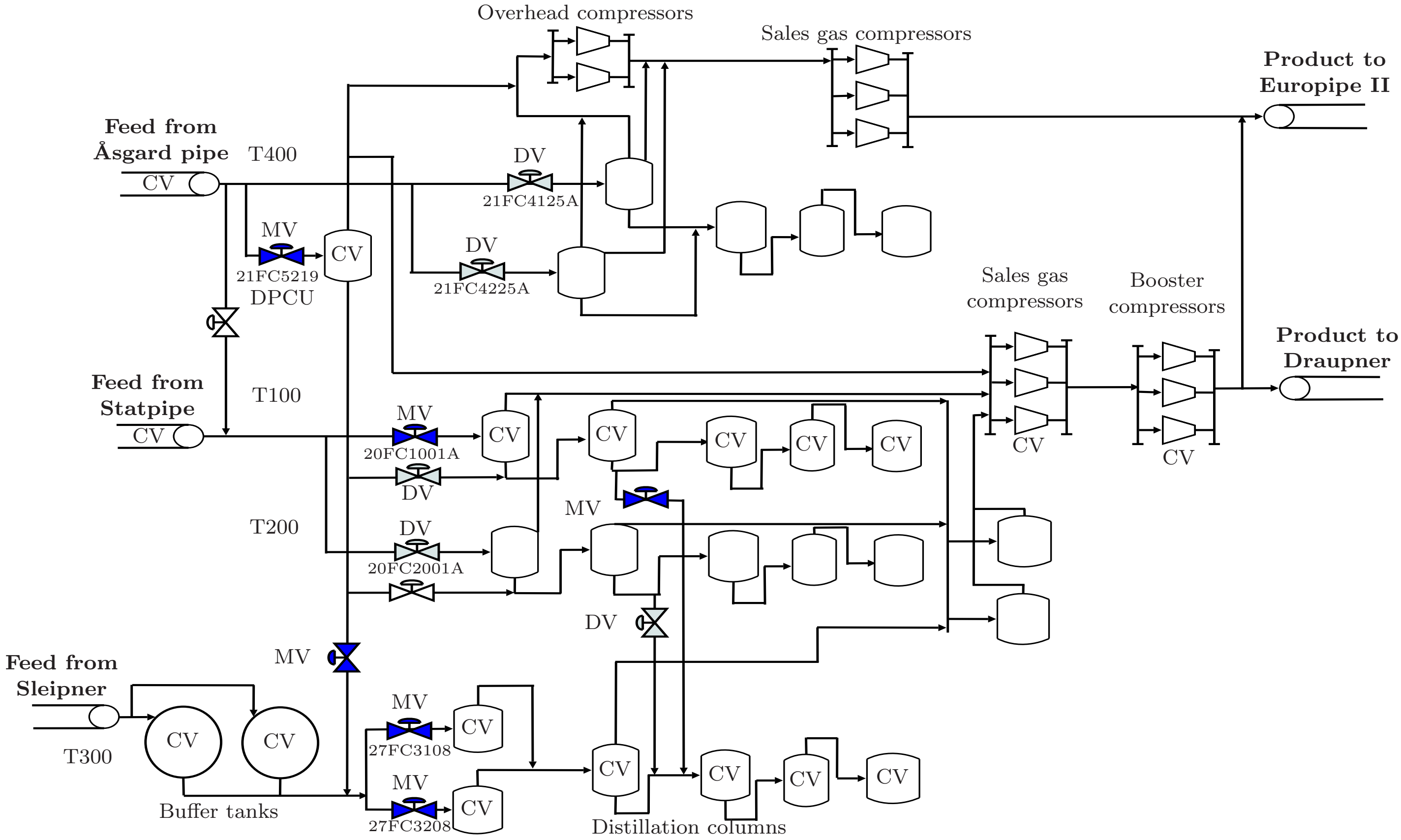

Fig. 2. Overview of the Kårstø plant, including the coordinator MPC variables.

even if parts of the plant are not running or not available for throughput maximization.

The decomposition requires that the coordinator receives three variables from each of the 12 local MPC applications:

- Estimated remaining capacity (value)
- Quality of the remaining capacity value (good/bad)
- Status of the local MPC (on/off)

If the estimated remaining capacity has a bad value, that is, the LP formulation is not feasible, then the status of the remaining capacity CV is set to ERROR and the corresponding MVs, given by the sub-grouping in the coordinator, are then suspended. If a local MPC application is deactivated, then the unit remaining capacity CV is set to OFF in the coordinator and the sub-group in the coordinator is suspended. The coordinator still runs, but the MVs in the sub-group are deactivated. This is done because we require that the local MPC application is active before the coordinator can manipulate on the corresponding unit feed rate.

4.2 Dynamic modelling for the coordinator MPC

The model for the coordinator MPC is a linear dynamic model for the flows through the plant network with the local MPC applications in service. The current implementation of the coordinator uses individual (SISO) step response models, or more precisely a single-input multiple-output representation of a multi-input multi-output system. The advantage with SISO models is that it is easy to adjust the models independently for input-output pairs. However, SISO models imply that the structure of the model is lost and, for instance, disturbances may not propagate as they would in a state-space model. The loss of structure leads to some additional variables around the DPCU.

The models are obtained from step tests and historical plant data. The steady-state gains found from step-tests are verified by calculating the gains using typical feed compositions.

The sampling time for the coordinator MPC is 3 minutes. The prediction and control horizon are set to 6 hours, whereas the longest response models reach steady state at approximately 4.5 hours.

4.3 Tuning the coordinator MPC

The tuning of the coordinator MPC is a trade-off between robustness and MV (e.g. feed) variations on one side and keeping the flows through the bottlenecks close to their maximum on the other side. The coordinator MPC was gradually operating in closed-loop and tuned in several tests in February 2008.

MV tuning From the early tests, it became clear that the trick of using a CV of total plant feed with a high, unreachable set point to maximize throughput, requires ideal values on the MV plant feeds to obtain satisfactory dynamic performance. The ideal values that are added to the MV plant feeds are high and unreachable with a lower priority than the total plant feed set point and have a low penalty on the deviation from the ideal value. The ideal values are needed to avoid that *all* MVs that constitute the CV total plant feed (see (2)) are reduced dynamically to reach the new recalculated set point for CV total plant feed.

When ideal values (IV) for the MVs are introduced, the rate of change towards the ideal value is specified to obtain ramping rate independent of the penalty on the deviation from ideal value (Strand and Sagli, 2003). The ideal ramping rate is typical set to 500-750 kg/h. Maximum increase and decrease of the MV at each sample is chosen based on typically rate changes operators choose to implement.

CV tuning The most important tuning variables for the CVs are the penalties on constraint violation used in the dynamic step of the MPC algorithm. The constraint violation is "balanced" by using penalties on MV moves to obtain a satisfactory dynamic behavior when CV constraints are violated. Even though a CV constraint is violated, the use of MVs should not be too aggressive to avoid unnecessary throughput variations. Importantly, the CV constraints are not absolute because back off is included to handle disturbances and imperfect control. Specifically, the lower value of the remaining capacities is not set to zero, but rather to a positive back off value, $R_k^l > \text{back off}_k > 0$. The value of the back off is a tuning parameter decided by disturbance handling and model accuracy.

The coordinator MPC has four integrating CVs; two buffer volumes (levels) and two pipelines pressures. For an integrator, the horizon length is a tuning parameter. A shorter horizon length will give a larger slope and allow for larger feed rate changes. The integrating variables have a prediction horizon of 3 hours, which is half the prediction length to the other variables. The prediction horizon is shortened because it is likely that disturbances occur within the 6-hour period that counteracts the change in the integrated variable.

5. EXPERIENCE FROM IMPLEMENTATION

Some experiences from the implementation at the Kårstø site are summarized in this Section.

5.1 Estimate of remaining capacity

For distillation columns that frequently operate close to their capacity limit, the estimated capacity is generally good. For these units we have more experience in the actual operation range, and the models in the local MPC applications are typically obtained in this range. For some columns, the differential pressure is included in the remaining capacity calculation and this improves the estimate.

For control, the initial response for the models is most crucial to obtain good performance. For remaining capacity estimate, the steady-state model gain is most important. A systematic evaluation of the inferential models (estimators of product quality) and models in the local MPC applications is necessary to obtain satisfactory performance of the coordinator MPC. Since some of the local MPC applications were commissioned several years ago, a validation of the models was found necessary.

One observation is that when a large disturbance occurs, the predicted steady-state values may violate their limits and, if this violation is sufficiently large, the LP optimization does not find a feasible solution and the estimate of maximum capacity ($F_{k,max}^l$) fails. The end prediction values are in such cases often not reasonable because the MPC application assumes that the disturbances will maintain constant (possible reduced with a low-pass filter) throughout the prediction horizon, which is rarely the case.

To improve the estimation of remaining capacity, several approaches are used:

- With a known, measured, short-time disturbance: The maximum capacity ($F_{k,max}^l$) is held constant during the period of the disturbance. For example, this is used for the disturbances that occur at each dryer exchange.
- For each unit, a minimum value of the maximum capacity ($F_{k,max}^l$) is included.
- CV constraints included in the local MPCs that should not limit the throughput were replaced with wider constraints. This applies to "non-physical" constraint that may have been added in the MPC for tuning reasons.
- Gain scheduling is included for some differential pressure models.

The main structural weakness in the estimation of remaining capacity is that the LP solver may "give up" to find a solution because there is no possibility for relaxation of constraints. When the LP solver does not find a solution, it returns a "bad quality" value to the coordinator and its variable subgroup is turned off. It would be preferable that the coordinator finds the best possible solution instead of "giving up". This can be realized with a LP solver that includes relaxation of the constraints. This improvement of the LP algorithm is planned to be included in the future.

5.2 Experience with the coordinator MPC

A test run of the coordinator MPC from 07 Feb. 2008 is displayed in Fig. 3. The coordinator is turned on at $t = 18$ min and the coordinator starts to increase the feed to T100 (Fig. 3(a)) until the pipeline pressure in Statpipe reaches its low constraint (Fig. 3(b)). During this start-up period, the crossover flow ramps towards its ideal value (Fig. 3(c)). The remaining capacity in the butane splitter T100 reaches its low constraint (Fig. 3(d)) and the crossover increases again to avoid reduction in the throughput. However, the use of the crossover is "aggressive" and actually generates oscillations in the downstream remaining capacities. The model gain was almost doubled around $t = 250$ minutes and the crossover is now able to control the remaining capacity towards its low constraint. The adjustment of the model gain was based on comparing the model prediction (not shown) and actual value.

The accuracy of the estimate of remaining capacity for demethanizer T100 (Fig. 3(e)) was poor. The model gain from column feed to differential pressure was increased at $t = 320$ minutes, and the new value seems to give a more correct estimate of the remaining capacity for the column. Again, the adjustment of the model gain was based on comparing model prediction and the actual value. Note that the remaining capacity of the demethanizer T100 became close to zero at about $t = 330$ min and the lower constraint value (back off) was increased at $t = 500$ min to obtain larger operation margins.

Feed composition changes are important disturbances and affect the remaining capacity to the units. The feed composition in the Statpipe (T100) (Fig. 3(f)) is rather stable until $t = 580$ min when the feed becomes significantly heavier and thereafter (at $t = 610$ min) significantly lighter. In this case, the coordinator uses the crossover (Fig. 3(c)) and the T100 feed rate (Fig. 3(a)) to control the remaining capacity for the butane splitter T100 (Fig. 3(d)) at its constraint.

When in closed loop, the coordinator MPC manipulates directly on the plant production. This directly involves the shift manager at Kårstø and close cooperation with the manager at the gas pipeline network (operated by another company) is necessary. The plant is operated by three control panels, so a close dialog between the operator personnel and the shift manager is crucial. The coordinator MPC introduces a “new way of thinking” for both operators and shift managers. The coordinator introduces the back off constraint as a new handle in addition to pressure pipeline constraints, instead of the feed valves.

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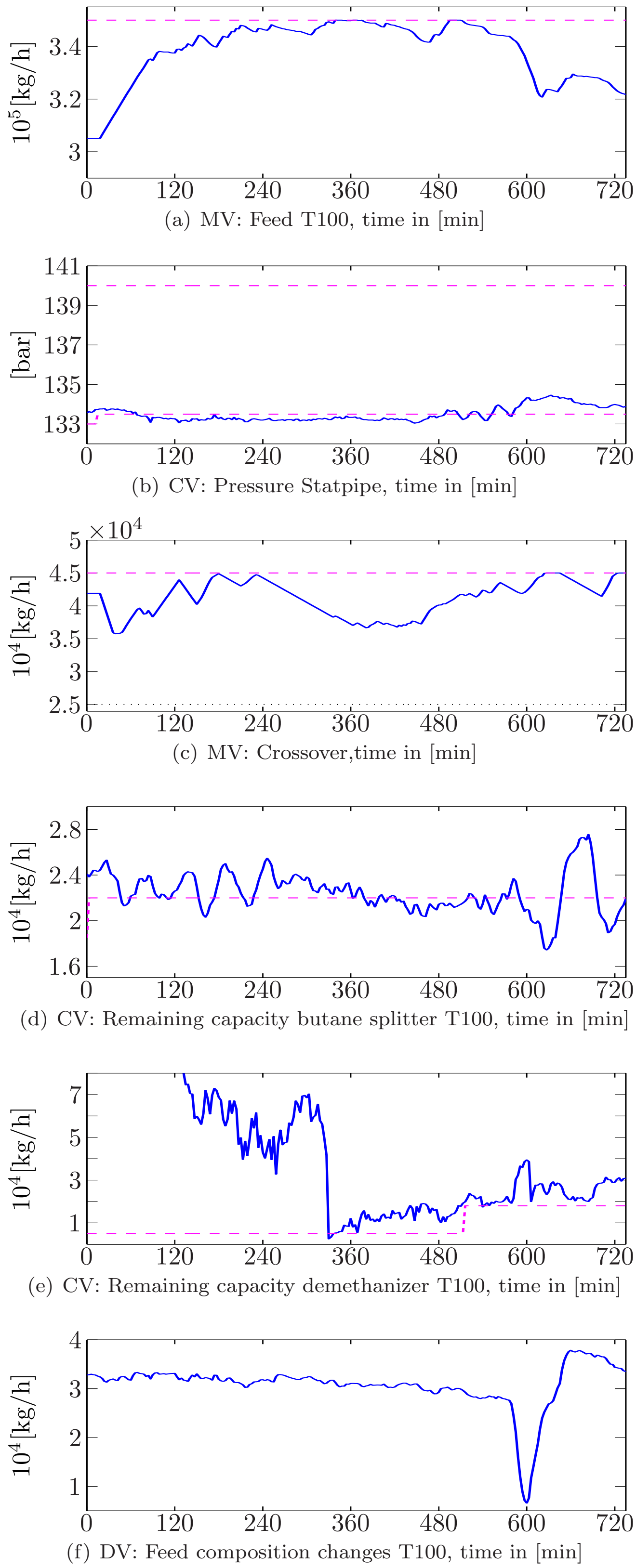

Fig. 3. From test run 07 Feb. 2008: $t = 18$ min: turn on, $t = 250$ min: change in model gain for crossover, $t = 320$ min: change in model grain for feed to differential pressure in the demethanizer, $t = 580$ and $t = 610$ min: feed composition change. MV and CV values (solid), high and low limits (dashed) and ideal values (dotted).