

Coordinator MPC with focus on maximizing throughput

E.M.B. Aske^{ab}, S. Strand^b and S. Skogestad^{a*}

^aDepartment of Chemical Engineering, NTNU, N-7491 Trondheim, Norway

^bStatoil R&D, Process control, N-7005 Trondheim, Norway

In this paper we suggest a "coordinator MPC" to perform dynamic real-time optimization (DRTO) on a plant. We consider the case where the plant economic criteria can be simplified to maximize the throughput in the plant. A measure for the distance to the bottleneck is formulated for a distillation column and the responses from feed to remaining capacity are expressed by experimental step-response models. The coordinator is demonstrated on a dynamic simulator and performs well for the simulated challenges.

Keywords: MPC, coordinator, dynamic optimization

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 [1]. When disturbances of economic importance have a dynamic character and especially if they occur frequently compared to the controlled plant responses, steady state RTO will be inadequate to follow the optimal operation point in periods. In such cases DRTO is more suitable, and different authors have discussed this subject.

Steady state assumption in conventional RTO severely limits the frequency of optimization in integrated plants, leading to suboptimal economic performances [2]. One argument for this is that integrated plants have very long transient dynamics, so once a change occurs, it may take a very long time for the plant to reach the new steady state, thus limiting the execution frequency of the RTO. Second, optimal operating conditions calculated from a steady state model may be suboptimal or even infeasible at the local units due to the transient dynamics, unit interactions, model errors and disturbances. Third, dynamic degrees of freedom may be left unexplored leading to suboptimal dynamic solutions.

Many researches have suggested that DRTO is performed at the same rate as the local unit controllers. [3] presents an approach where DRTO and MPC into a single layer by adding an economic objective function to the control objective function of MPC in a weighted average manner. Determining weighting factors and robust tunings is, however, a time consuming task.

A systematic approach for integrating DRTO and MPC for large scale-industrial processes is presented by [4]. The two tasks, economic trajectory optimization and control, are decomposed into an upper layer dynamic trajectory (re)-optimization, and a lower level (nonlinear) MPC that controls the process along the current optimal trajectory determined by the upper level. Re-optimization is not necessary at each optimization sample time, instead it can be based on the disturbance dynamics.

The wide use of MPC establishes a solid foundation for large-scale optimization. Dynamic coordination among MPC controllers is a key to tight integration between advanced process control and plant wide optimization [5]. In this paper we suggest to use a "coordinator MPC" with simple experimental models to solve a dynamic optimization problem for a plant. In this case, the structure of the optimization problem makes MPC an applicable tool for solving the DRTO problem.

*Corresponding author: skoge@chemeng.ntnu.no

2. COORDINATOR MPC

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. The coordinator MPC is placed above the local MPCs in the control hierarchy and coordinates the underlying MPCs. The coordinator can perform as a DRTO if the plant economic criterion is of such kind that it can be formulated as a controlled variable (CV) in the MPC. It operates with feedback on minutes basis, compared to the typical RTO execution time of several hours. This leads to a faster correction of disturbances, model errors and transient dynamics.

Most plants today operate without an RTO layer. Implementing a coordinator MPC requires less modeling effort compared to implementing RTO, but can still give a large part of the earnings. Even if RTO is implemented on the plant at a later stage, it can be combined with the coordinator MPC. 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 the dynamic transfer to the steady-state optimum if that 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 modeling and maintenance. Introducing an extra layer in the hierarchy with smart decomposition reduces this complexity.

3. BOTTLENECK

For several plants, it is optimal to maximize the throughput (production rate), subject to achieving feasible operation. Feasible operation is defined as satisfying given constraints on product qualities, flow rates, capacity, temperatures, pressures, etc. We have not defined "throughput", but for cases with a single feed it is equivalent to maximizing the feed rate integrated over a given time of operation. For cases with multiple feeds, the throughput may correspond to a (weighted) sum of the individual feeds, but the details will depend on the process and economics.

When the feed rate to a process is increased, one will eventually reach a (maximum) value where feasible operation is no longer possible. This occurs as we reach a bottleneck somewhere in the plant. More precisely, we have the following definition: *A bottleneck is as a constrained extensive variable, where the maximum value prevents an increase of the plant throughput (capacity, production rate, overall feed), subject to achieving feasible operation.* Examples of bottlenecks are the neck of a bottle, and a 1-lane bridge on a 2-lane road. The location of the bottleneck for a given plant may change depending on external factors (disturbances) such as feed composition.

If the objective is to maximize throughput, then it is generally optimal to set the throughput at the bottleneck [6]. The reason for this is dynamic. As an example, consider the 2-lane road with a 1-lane bridge. At steady-state the number of cars in (feed) and out (product) are the same. However, dynamically they may vary, and it is clear that in order to maximize the throughput of cars, we must make sure that we always have the maximizing flow at the bottleneck, that is, on the 1-lane bridge. If we for some time do not have the maximum flow through the bottleneck, then this loss in throughput can not be recovered later. The same applies in a chemical plant. However, one problem with this is that if the location of the bottleneck changes, then this generally requires reconfiguration of the basic control loops for inventory (level) control, which is undesirable. Therefore, in practice, and as discussed in this paper, we may need to adjust the throughput at some other location, for example at the feed, while trying to keep the flow at the bottleneck as close to its maximum as possible.

4. REMAINING CAPACITY AND THE OPTIMIZATION PROBLEM

Assume the objective is to maximize the overall throughput. One approach is to set up a large optimization problem (RTO) and find the optimal solution. However, it is desirable that the coordinator does not have to duplicate the models and constraints in the local MPCs, so a more decoupled solution strategy is wanted. Since the location of the bottleneck may change, it requires an overview of the available capacity in each part of the plant. With MPC installed on each unit we may use this tool to obtain the available unit capacity.

We suggest that the steady state part of the local MPC on unit k is extended to obtain an estimate of the remaining capacity in the unit

$$R_k = J_{k,max} - J_k \quad (1)$$

where J_k is the current throughput (feed) in unit k . The maximum feed rate $J_{k,max}$ may be solved by solving a simple LP optimization. The constraints in the LP problem are the same as in the steady state solver in the local MPC, only the objective function is different.

The LP calculation in each local MPC returns to the coordinator the remaining capacity R_k in each unit. The optimization at the coordinator level is to maximize the weighted overall feed rate:

$$\max_{MV} J = \sum w_i F_i \quad \text{subject to} \quad R_k \geq 0; R_k = G * MV \quad (2)$$

where J is a weighted sum of the feed rates to the plant. The manipulated variables (MVs) at the coordinator level are typically the external feed rates and crossovers in the plant. G represents the dynamic influence from each MV to R_k .

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 constraint back-off should be set according to the controller performance and the acceptable constraints violations. 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 value of J , but makes the coordinator more robust.

Control target/range changes in the local MPC, like MV and CV limit changes, have a direct influence on the remaining capacity measure and must also be handled by feedback with the given 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 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 is included in the calculation of remaining capacity.

5. KÅRSTØ GAS PROCESSING CASE STUDY

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®.

5.1. The case

To demonstrate the applicability of the coordinator MPC, we use a detailed simulation model of parts of the Kårstø plant. The 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 1. 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 by valves in Figure 1. The local MPCs and the coordinator are implemented in SEPTIC² MPC software [7]. For description of the local MPCs, see [8].

5.2. Coordinator MPC

The coordinator task is to maximize the plant throughput within feasible operation. Maximizing flow rate can be realized with our standard quadratic objective function by a total plant feed as a CV with a high (not reachable) set point with lower priority than the capacity constraints. The inputs and outputs of the coordinator MPC are as follows:

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

²Statoil Estimation and Prediction Tool for Identification and Control

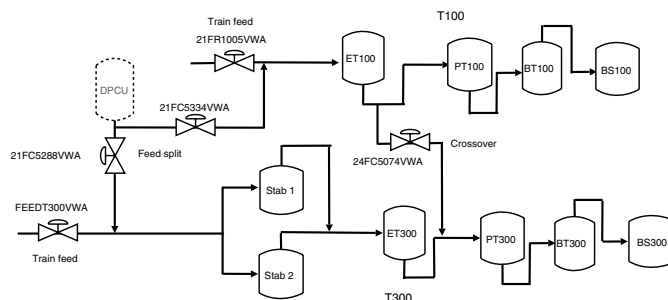


Figure 1. The simulated parts of the Kårstø plant

- MVs: Feed flow from DPCU to T-100 and T-300 (21FC5334VWA, 21FC5288VWA), train feed flow T-100 (21FR1005VWA), train feed flow T-300 (FEEDT300VWA) and crossover flow from T-100 to T-300 (24FC5074VWA)

The total plant feed is defined as the sum of the train feeds and DPCU feeds. 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 column capacity is calculated in each local MPC as an LP problem considering CV and MV constraints around the column. The column feed is a free variable in the LP formulation and the flooding point is represented by a high limit on the column differential pressure.

The execution is set to a slower rate than 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. The composition is measured with gas chromatograph (GC) at the plant feed inlets and in top of the distillation columns. However, the dead time in the GC sampling makes the measurements unsuitable for control. The feed composition changes are therefore characterized as unmeasured disturbances.

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 a common operation area for the real plant. The coordinator MPC tuning is a trade-off between MV 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 constraint back-off will be necessary.

5.3. Results from the simulator case study

The coordinator performance is illustrated with three different cases, and the CVs in the coordinator MPC are shown in Figure 2 whereas the MVs are displayed in Figure 3.

Move the plant to maximum throughput. The coordinator is turned on at $t = 0$ minutes to move the plant operation from a non-optimal to an optimal operation point. Figure 2 shows that the deethanizer in T-100 and the stabilizers are bottlenecks at the optimal operation point. The butane splitter in T-300 reaches its capacity limit, however, there is available capacity in the depropanizer and downstream columns of T-100 and the coordinator uses the crossover to reroute, removing the T-300 butane splitter bottleneck.

Change in feed composition. A momentary feed composition change is introduced in the T-100 feed at $t = 360$ minutes. The feed composition change increases the remaining capacity of the T-100 deethanizer and makes it possible for the coordinator to increase the train feed. The disturbance reduces the remaining capacity in the butane splitter so the coordinator uses the crossover to keep the column within its capacity. However, the butane splitter in T-100 is not a plant bottleneck yet, since there is still capacity for rerouting to T-300.

Change in a local MPC CV limit. With the butane splitter in T-100 operating at its capacity limit, the

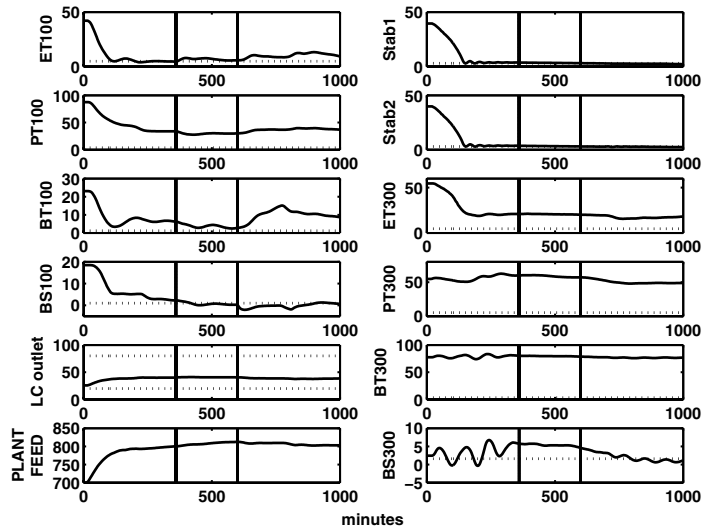


Figure 2. CVs in the coordinator MPC, remaining capacity and plant feed in t/h

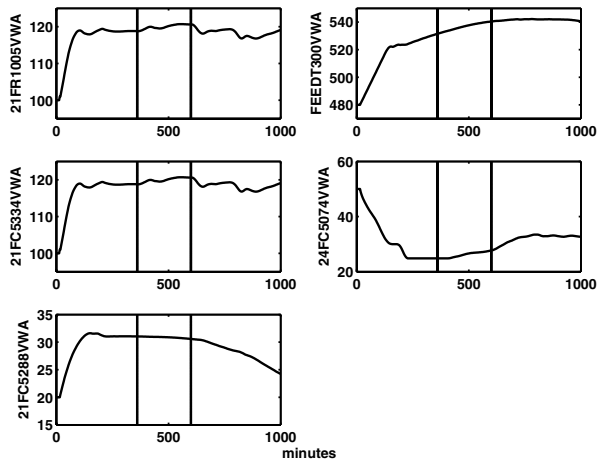


Figure 3. MVs in the coordinator MPC, flows in t/h

operator reduces the bottom quality high limit in the local MPC at $t = 600$ minutes. The coordinator increases the crossover since there is available capacity in the T-300 string, but must also reduce the T-100 feed some. Both the butane splitters are now bottlenecks in the plant, together with the stabilizers.

6. DISCUSSION

The coordinator MPC is demonstrated on a dynamic simulator and performs well for the simulated challenges. Back-off reduces the optimal function value, but is necessary due to unmeasured disturbances and the long process response times.

An improvement of the coordinator MPC is to include some feed forward especially from feed composition changes. Split fraction in the column can be used, then both feed composition changes and upstream processing units operation changes will be detected. Including feed forward information, the back-off in the coordinator could then be reduced leading to a larger plant throughput.

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. Significantly model changes including dynamics, other model types in the coordinator MPC should be evaluated.

Another weakness with the coordinator MPC is the simplified maximum throughput objective function. This is a special case, and if the feed turns to be limited for a period, the economic optimum will be different since energy costs and product prices should be included in the objective function. In such a case the coordinator will not lead the plant to optimal operation. Further, the buffer capacity in the distillation columns are not exploited. Faster responses can be obtained by active use of the buffer volumes, leading to a smaller loss in the economic objective function. In this simulated case the buffer volumes are limited, however, in other plants with larger buffer volumes this should be considered. Other linking variables between the units can also be considered, like increasing impurity in a column to decrease the load to the downstream unit. At last, the simplified coordinator MPC will be inadequate for longer-term planning purposes, where a more traditional RTO model will give valuable information.

7. CONCLUSION

In this paper we suggest to use a coordinator MPC with experimental step response models to optimize a plant with disturbances of dynamic character. The plant economic object function is simplified to maximize throughput in this case with a gas processing plant as case study. The coordinator MPC is designed and set up in a simulator together with unit MPC applications and performs well for the simulated challenges.

REFERENCES

- [1] Y. Zhang and J.F. Forbes. Extended design cost: a performance criterion for real-time optimization systems. *Comp. Chem. Eng.*, 24:1829–1841, 2000.
- [2] T. Tosukhowong, J.M. Lee, J.H Lee, and J. Lu. An introduction to a dynamic plant-wide optimization strategy for an integrated plant. *Comp. Chem. Eng.*, 29:199–208, 2004.
- [3] M. Tvrzská de Gouvêa and D. Odloak. One-layer real time optimization of LPG production in the FCC unit; procedure, advantages and disadvantages. *Comp. Chem. Eng.*, 22:S191–S198, 1998.
- [4] J.V. Kadam, M. Schlegel, and W. Marquardt. A two-level strategy of integrated dynamic optimization and control of industrial processes - a case study. *ESCAPE-12, The Hague, The Netherlands*, pages 511–516, 2002.
- [5] J.Z. Lu. Challenging control problems and emerging technologies in enterprise optimization. *Control Engineering Practice*, 11:847–858, 2003.
- [6] S. Skogestad. Control structure design for complete chemical plants. *Comp. Chem. Eng.*, 28:219–234, 2004.
- [7] S. Strand and J.R. Saggi. MPC in Statoil - Advantages with in-house technology. *ADCHEM 2003, Hong Kong*, pages 97–103, 2003.
- [8] E.M.B Aske, S. Strand, and S Skogestad. Implementation of MPC on a deethanizer at Kårstø gas plant. *16th IFAC World Congress, Prague, Czech Republic*, 2005.