# MPC: Current Practice and Challenges

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**Abstract:** Linear Model Predictive Control (MPC) continues to be the technology of choice for constrained multivariable control applications in the process industry. Successful deployment of MPC requires "getting right" multiple aspects of the problem. This includes the design of the regulatory controls that receive setpoints from MPC, design of the multivariable controller(s) themselves, test design for model identification, model development, and dealing with nonlinearities. In the following, we highlight approaches and techniques that are successfully applied in practice and provide an overview of recent technological enhancements that are being made to MPC. While significant progress has been made in both the technology and practice, there are challenges with MPC, mostly related to the effort required to develop an application and to ensure adequate performance over time. Suggestions for addressing these issues are included as possible research directions.

*Keywords:* model predictive control, model-based control, constraints, control system design, modeling, process identification.

## 1. INTRODUCTION

Model predictive control (MPC) is a mature technology. It is the standard approach for implementing constrained, multivariable control in the process industries today. MPC provides an integrated solution for controlling interacting systems with complex dynamics and constraints. A key aspect of MPC is its ability to deal with degrees of freedom, that may arise when there are more or fewer inputs (manipulated variables) than outputs (controlled variables), or when zone limits for controlled variables are used, which is the typical situation in practice. Broadly defined, MPC refers to a control algorithm that explicitly incorporates a process model to predict the future response of the controlled plant. While the model may be linear or nonlinear, we consider linear MPC as it is used in the majority of industrial applications in the refining and petrochemical industries today (and increasing, in other industries). For these applications, the plant model is identified based on data generated from a dedicated plant test. Today, there are a number of technology vendors which provide MPC solutions, including software to facilitate the development of MPC applications and monitoring of the performance of these applications over time. The last 10-15 years has seen significant efforts by technology suppliers to improve the usability of MPC products.

While the "science" of MPC has advanced and the technology is now easier to apply, there is still an "art" aspect to the application of MPC that largely comes from experience. The success of an MPC application depends on the multiple technical decisions that are made by the control engineer in the course of an implementation. In addition, there are both technical and organizational issues that are critical to ensuring that MPC benefits are sustained in the longer term once an MPC is commissioned (Darby and Teeter, 2005). Based on our experience, we find that the success rate of MPC across the industry is uneven. Some companies are consistently successful in deploying MPC, whereas others are not. In the following, our main emphasis concerns the technical aspects of MPC that arise in the course of an implementation.

MPC is positioned above a regulatory control level as shown in Figure 1. The manipulated variables for the MPC are typically setpoints of PID controllers, executed in a distributed control system (DCS). The MPC may also directly manipulate valve position signals rather than, e.g., flow.

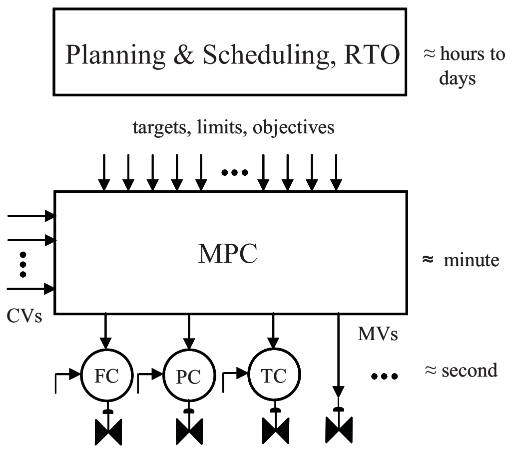


Figure 1. Control hierarchy

The DCS executes a at a higher sampling rate than the MPC, typically sub–second to multi-second sample time, compared to a 30 sec to 2 min execution period for MPC.

Certain targets and objectives for MPC come from higher level functions such as planning and scheduling, typically communicated to the operator in an open-loop fashion, or from a real-time optimizer, if present. Note that there it not necessarily a one-to one-translation of decisions from upper level functions to targets and limits in the MPC. Economic objectives and priorities may also be involved. Examples include gasoline vs. diesel objectives (winter vs. summer) in a refinery and the priority of feed stocks in an ethylene plant. In addition, there are day-today issues that may arise such as a late shipment, or a product tank becoming full.

Part of the challenge in implementing MPC is that the regulatory control layer is not a given (or should not be taken as a given). The design problem is really one of deciding on the best overall structure for the regulatory level *and* MPC, given the control objectives, expected constraints, at least qualitative knowledge of the expected disturbances, and robustness considerations. Similarly, the selection of the controlled variables for MPC is not one of simply deciding which subset of available measurements should be selected. It may be that available measurements are insufficient and additional sensors are needed. In addition, not all variables that need to be controlled may be available on a frequent-enough basis; therefore, we have the problem of inferring qualities from secondary measurements. The above decisions are by no means trivial and represent key aspects of the controller synthesis problem that have attracted significant attention over the past four decades (Buckley, 1964; Weber and Brosilow, 1972; Morari et al., 1980; Larsson and Skogestad, 2000; Stephanopoulos and Ng, 2000).

Once the regulatory level is decided upon, the remaining decisions relate to how to structure the MPC layer: Should one controller or multiple MPC controllers be used? For each controller, there is the issue of deciding on the manipulated variables, the controlled variables, and the feedforward variables. Non-linearities are other issues that must also be addressed, if significant in an application. Note that the techniques discussed here are based on approaches that retain a linear(ized) dynamic model at the core of the MPC engine.

The typical MPC project sequence is as follows:

Pretest and Preliminary MPC design.

Plant Testing.

Model and Controller Development.

Commissioning and Training.

In the pretest phase of work, the key activity is one of determining the base level regulatory controls for MPC, tuning of these controls, and determining if current instrumentation is adequate. The outcome of this phase is a list of issues that must be fixed or resolved before plant testing can proceed. Typical problems that are identified are valve issues (sizing and excessive valve stiction), faulty instruments, and sensor location. The other task that begins in this phase is one of learning the process and understanding the operational challenges and expected constraints. In addition, a preliminary design for the MPC is typically performed, i.e., identification of controlled and manipulated, and number of MPCs.

Plant testing consists of generating plant data for model identification. Additional process knowledge and insight comes from this phase of work. Testing requires moving all inputs that may be manipulated variables for the MPC. Testing may be performed manually or automatically. During this phase of work, frequent lab measurements are collected, if an inferential model of product qualities is required.

In the next phase or work, modeling of the plant is completed, including any required inferential s and non-linear compensators. It is here that the models are analyzed for consistency. The final design for the controller or controllers is completed and simulations performed to test the model and tune the controller.

Commissioning involves turning on the controller and observing its performance on the plant and making tuning adjustments as needed to obtain a properly functioning controller. Training of operations staff on the live controller is begun in this phase.

In the following, we provide a high level description of MPC, MPC, without much emphasis on the particular theoretical properties of the MPC algorithm, for which there is already a substantial body of work (Mayne et al., 2000.). Subsequently, we present a detailed discussion of the key tasks and decisions that are made in the course of an implementation. Where appropriate, current practice is highlighted and guidelines are given. The impact of recent technological enhancements that have appeared are discussed. Lastly we suggest areas where improvements may be made.

## 2. MPC OVERVIEW

A simplified block diagram of the typical MPC is shown in Figure 1. Key functionality of the components shown in the figure are described below.

<u>Target Selection</u>: Target selection determines the best feasible, steady-state operating point, $\mathbf{x}_k^s, \mathbf{u}_k^s$ based on steady-state gains of the model. It can be implemented on the basis of minimizing deviations from desired steady-state "resting values" or as the result of an economic-based steady-state optimization, typically either a linear program (LP) or a quadratic program (QP).

<u>Controller</u>: The controller determines optimal, feasible future inputs to minimize predicted future errors, over a moving horizon, from targets determined by target selection. Tuning parameters (e.g., weights) are used to establish the dynamic

objectives and trade-offs. A QP is typically used to perform the controller optimization.

Estimator: The estimator updates the model estimate to account for unmeasured disturbances and model errors. It includes a deterministic part that models the effect of controller-manipulated process inputs (and other measured process inputs) on the process outputs, and a stochastic part (which may only be implicit) that models the effect of unmeasured disturbances on the process outputs. The simplest form for the estimator is the original MPC output correction (and still widely used today), where the current offset between the measurement and the model prediction is used to bias future model predictions. A state space model represents a more general and flexible approach to modeling unmeasured disturbances in the estimator.

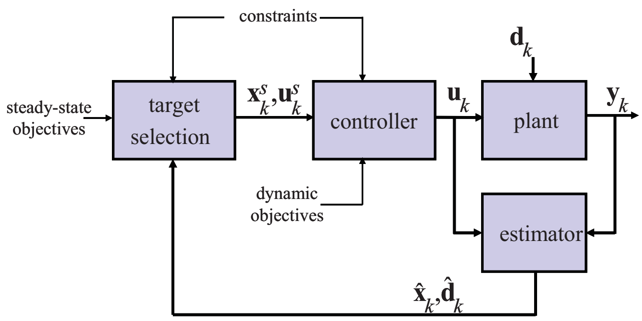


Figure 2. Simplified MPC block diagram

Various model forms are used in the various MPC products available today. Most common are the finite step response (FSR) or finite impulse response (FIR), but state space model formulations are also found. Recent controller products suggest a trend towards increased use of state space model formulations, because of the flexibility they offer to represent stable, integrating, and unstable processes in a single structure.

Our intent is not to delve into differences between the formulation and options of the various products. The interested reader is referred to Maciejowski (2002) and Qin and Badgwell (2003) Suffice it to say that differences exist among the products as to the approaches taken, but that they address important features such as prioritization of constraints, economic objectives and tuning parameters to influence CV vs. MV variance trade-offs. Most MPC controllers today force consistency between the sequence of input moves generated by the controller and the steady-state solution determined by the target selection. This consistency, which is equivalent to the imposition of a terminal constraint, provides nominal and robust stability (Genceli and Nikolaou, 1993; Rawlings and Muske, 1993; Ying and Joseph, 1999)

## 1. DCS STRATEGY

In deciding upon an appropriate DCS strategy for the MPC, there are several factors that need to be considered and balanced. Major factors are disturbance rejection, process interaction, robustness to model errors, and constraint considerations. Another factor is the influence of the DCS strategy on the settling time of the system, which affects the control horizon in MPC.

Fortunately, when implementing MPC, an existing DCS strategy is in place that can be evaluated and changed, if necessary. We are aware that some practitioners choose to use existing DCS schemes "as is" as opposed to modifying or pairing the PID loops in a different way. However, such modifications can have a significant impact on both MPC control performance and the ease of implementation (e.g., testing). Note that with modern DCS systems a different DCS strategy ("fall-back") may be used when MPC is switched off or fails.

A typical decision concerns whether to incorporate a cascade, such as temperature to flow cascade on a distillation column, or a temperature to pressure cascade on a direct-fired heater. As we have discussed, the DCS typically operates at a higher sample frequency than the MPC; therefore an existing cascade, if tuned well, will likely have much better disturbance rejection capability than the MPC. An additional advantage is that a cascade may help to linearize important CVs controlled by the MPC (because of the linearizing effect of feedback in the inner loop in a cascade scheme). This can be advantageous in providing acceptable control over a wider range of, e.g., plant feed rates.

The thinking with respect to cascades with MPC has clearly evolved over the years. In earlier days of MPC, it was often thought preferable to "break" an existing TC cascade and design the MPC to manipulate flow controllers. The motivation was that this would lead to simpler (overdamped) models and allow the interaction to be addressed by the MPC. What was missed with this approach was the rejection capability of the DCS via the higher sampling frequency, and the robustness that results from incorporating a TC into the MPC strategy. Consider the case of the two-by two subsystem associated with the product purities of a binary distillation column, controlled in the reflux-boilup configuration (so called *L-V* configuration). Consider two cases: 1), MPC control of compositions via *L* and *V* and 2) MPC control of the compositions via L and a stripping section TC controller that manipulates boilup. We assume that the controlled temperature correlates well with the bottoms product composition. The model relationships for these two cases are

$$\begin{bmatrix} y \\ x \end{bmatrix} = \begin{cases} L-V: & \begin{bmatrix} g_{11} & g_{12} \\ g_{12} & g_{22} \end{bmatrix} \begin{bmatrix} L_{sp} \\ V_{sp} \end{bmatrix} \\ L-TC: & \begin{bmatrix} g_{11}^{TC} & g_{12}^{TC} \\ g_{21}^{TC} \approx 0 & g_{22}^{TC} \end{bmatrix} \begin{bmatrix} L_{sp} \\ TC_{sp} \end{bmatrix} \end{cases} \tag{1}$$

Due to its lower triangular structure, *L-TC* is a more robust formulation compared to a full decoupling strategy with manipulated variable *L* and *V*, especially if the process is ill-conditioned, or more accurately, has large RGA elements (Skogestad and Morari, 1987). In most cases a temperature cascade would be retained if it performs well. In a distillation column, it may be necessary to select another tray temperature if the existing one does not correlated well with product quality. Note that dual-ended temperature controls would normally be avoided because of interactions and the potential for the controllers to wind up (i.e., saturate) , if a section of the temperature profile shifts to a region of insensitivity (e.g., due to a feed composition change).

Another cascade decision concerns level to flow cascades, associated with feed drums, reflux accumulator drums and distillation column sumps. The questions is: should a flow be controlled directly by the MPC (with the associated level controlled by the MPC)? A motivation for doing so is to obtain a direct handle on inflows, without the dynamics of the level controller. Such an approach is useful when a plant capacity constraint exists, such as column flooding, and unit feed rate is also manipulated by the MPC. By directly manipulating column feed, tighter control of a plant capacity constraint can be achieved by taking advantage of liquid holdup in intermediate drums. Additional justification is to shorten system settling time by removing the dynamics of level controllers.

A disadvantage of including levels in the MPC is that levels, which are integrating variables with respect to flow, are that they harder to keep in bounds during an open-loop plant test. Levels are affected by both material and energy balance effects. While material balance effects may be straightforward to model, energy balance contributions affects must also be modeled, which tend to contribute over a longer time frame. Part of the challenge with integrating variables is related to the identification problem, as it is common to identify the first difference of an integrating CV, which decreases the signal-to-noise content. Note: in some FIR-based ID methods a double difference is used - one difference for the integrator and an additional difference (for both inputs and outputs) to remove integrating or slow disturbance effects. An additional challenge is that it is common for an MPC controller to contain logic to switch off if an integrating variable cannot be balanced (zero difference) at steady state., thus making integrating variables more sensitive to measurement spikes.

An alternative to controlling the level in MPC is to keep the level cascade in the DCS and manipulate the level setpoint to influence the corresponding flow rate (taking advantage of buffering capacity). In this case, the level measurement could also be brought into the MPC as a CV (and controlled within bounds). For this situation, model relationship between level setpoint and flow is zero gain (i.e., dynamic response only, zero steady-state gain). We should note that practitioners are divided on what is the best approach, although most of the experience is with FIR- or FSR-based MPC. Examples of step response models for these two cases are shown in Figure 3.

We should note that the theory and experience-to-date indicate that integrating variables are more easily handled within a state-space formulation, as it allows more flexibility in the unmeasured disturbance model – i.e., selection of the disturbance channels and incorporation of additional output measurements (Qin and Badgwell, 2003; Froisy, 2009).

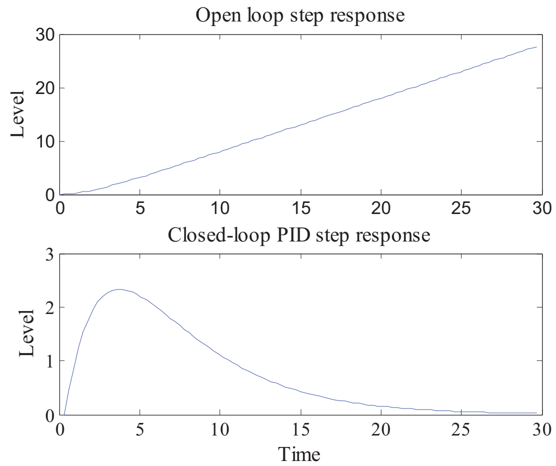


Figure 3. Step response models for integrating level: open-loop vs. closed-loop with PID

An important issue concerns valve positions of PID loops that are directly manipulated by MPC or that are affected by other manipulated variables of the MPC. For example, manipulating an FC controller setpoint will affect the valve position associated with the FC as well as the valve position associated with a downstream pressure controller. When a valve approaches a saturated state (either fully open or closed), not only is PID control lost for its associated controlled variable, but model mismatch (and nonlinearity) is introduced to all MPC-controlled variables that depend on the PID controller response. As a result, the MPC needs to keep PID controller outputs in a controllable range. This can be achieved by bringing the PID controller output into the MPC as a controlled variable. This approach is illustrated in Figure 3a. In this case, MPC manipulates the setpoint of the PID controller setpoint as necessary to keep the controller output in range. How well the PID output can be controlled and how close to saturation the MPC limit can be placed depends on: PID tuning, disturbances characteristics, and the degree of nonlinearity. It may be necessary to retune the PID loop based on the response of the controller output (a smooth response in the valve, without significant proportional "kick" is desirable).

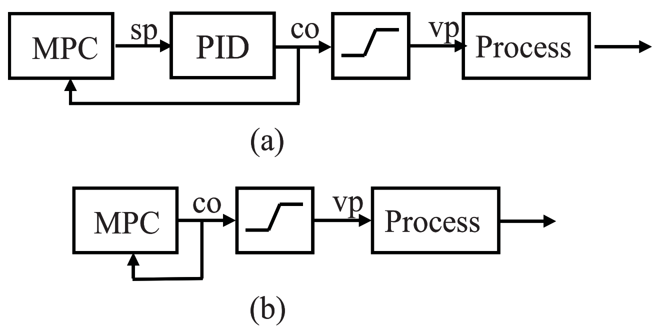


Figure 4. Alternate MPC strategies for maintaining valve positions in controllable range – (a) MPC to PID and (b) direct output to valve.

If a valve associated with a PID controller saturates more than 25% of the time, or if economics dictate operation at a fully open or closed-loop state, it may be preferable to directly manipulate the controller output directly, as shown in Figure 3b. In this way, the valve limit can be strictly enforced, resulting in control closer to the true valve limit. In this situation, additional disturbances may result from opening the PID loop that need to be addressed by the MPC

Regardless of the strategy, valves issues often arise in a project. Significant valve stiction (if greater than say 2%) must be corrected. In addition, valve nonlinearities may require compensation as part of the MPC strategy.

**Example** To illustrate how the various considerations discussed previously influence the MPC design, consider the two-column configuration shown in Figure 5, which is to be part of an MPC application that maximizes plant feed rate (not shown).

The following convention is used: ZC.sp denotes the setpoint of a PID loop to control Z; ZC.pv denotes the process variable or feedback variable for loop ZC; and ZC.op represents the output signal sent to the valve position.

For this example, assume it is known that the second column is susceptible to flooding, as indicated by a high value in DP1.pv, and that PC2op often saturates fully open. Because flooding is a constraint for column two, we would consider breaking the LC2 cascade and directly manipulating flow FC3.sp in the MPC. Due to the saturation potential of PC2, we would also consider directly manipulating its valve via PC2.op and controlling pressure within the MPC. If both temperature controllers perform well and the associated temperatures are good indicators of composition, they would be retained. These considerations then lead to an MPC with the following manipulated variables:

FC2.sp - column 1 reflux flow controller setpoint.

TC1.sp - column 1 temperature controller setpoint.

PC1.sp - column 1 pressure controller setpoint.

FC3.sp - column 2 feed flow controller setpoint.

FC5.sp - column 2 reflux flow controller setpoint.

TC2.sp - column 2 temperature controller setpoint.

PC2.op - column 2 pressure controller output.

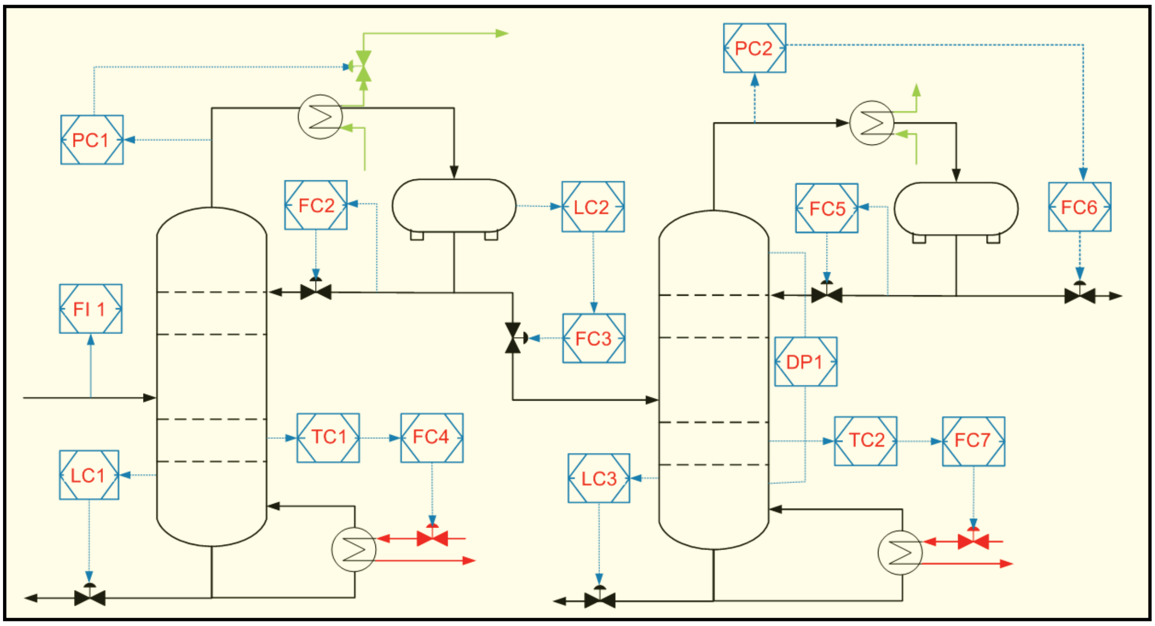

Figure 5. Example process to be controlled by MPC

## 2. PLANT TESTING

The plant test and subsequent model identification are the most important steps in an MPC project, and incur the most time, often representing more than 50% of the total project time. The importance of the accuracy of the plant model for MPC cannot be overstated. One cannot simply tune an MPC controller to compensate for a poor model. Further the effort involved in testing and identifying an MPC model is not a one-time event. To ensure adequate performance of an MPC application and sustain its benefits over time, it is necessary to re-perform plant testing to update the MPC model (all or in part) when control performance deteriorates due to a process change such as a process revamp.

Until the mid 90's, it was typical practice to conduct manual, open-loop tests, concentrating on the testing of one manipulated variable at a time, but moving other process inputs as necessary to maintain process operation in a desired region. Automatic testing via uncorrelated binary sequences such as PRBS or GBN increased in popularity in the mid to late 1990's, and closed-loop testing approaches started appearing in the early 2000's. Today we are witnessing increased use of multivariable closed-loop testing methods in the industry as a means to reduced costs (human effort and time) and improved model accuracy due to richer data sets. Of course, an initial model must be available to perform a closed-loop test. An initial model may be available from an existing controller; otherwise, an initial model may need to be developed (e.g., from pretest data).

All of the above testing methods continue to be used today. Some MPC engineers continue to advocate manual testing methods, arguing that it is more conducive to developing process knowledge. While this is indeed an important step, we believe that sufficient process knowledge can come from the pretesting phase and the early stages of an automatic or closed-loop test, where the testing may start with just a few inputs.

Regardless of the testing approach, it is important to generate data in the frequency range of interest. This requires varying the pulse widths of the input signals, e.g., from 10% to 125% of the estimated settling time. A typical guideline is to achieve an average pulse width of an (uncorrelated) input signal equal to 1/3rd of the open loop settling time of the process. Automatic signals can easily be generated to achieve a desired average pulse width. Input amplitudes are selected to keep process inputs and process outputs within desired ranges, but should be large enough to overcome valve stiction limits. Larger amplitude moves are preferred as long as the process responses remain within a linear range (unless linearizing transformations are used). A goal is to obtain a signal-to-noise ratio of at least 6-to-1.

The closed-loop testing approaches that have been developed for MPC also utilize uncorrelated binary signals. In Zhu (2001), generalized binary signals (GBN) (Tulleken, 1990) are applied to selected manipulated variables as dithers (added to MPC-generated manipulated variables) and to certain MPC-controlled variable setpoints. In Kalafatis et al. (2006), a closed-loop testing approach is described in which GBN binary signals are generated within the multivariable controller to maximize MV amplitude while keeping predicted CVs within preset constraints. Control action is only applied when predicted CVs exceed their limits.

Important quantities not measured online may require development of an inferential model. Generating data for inferential model development represents a much better approach than using only historical data, which typically has insufficient excitation and feedback effects. To ensure adequate data for model development, the process is moved to different steady-state operating values during the course of the plant test. Note that it is important to get accurate time stamps of the lab samples so that the data can be properly synchronized with measured plant test data for model identification. Due to the importance of the plant model, it is important not to stop a plant test prematurely. As a result, it is good practice to perform model identification throughout the testing phase until model quality is deemed adequate.

## 3. IDENTIFICATION METHODS

**Dynamic Modeling.** Various model structures are routinely used in the identification of models for MPC. Low order, parametric techniques continue to find application; however, these are nonlinear approaches, which require specification of model order (which is not straight forward). Processes with heat integration, recycle and/or embedded PID loops typically require higher order models to capture the resulting complex input-output behavior. As a result, we continue to find that finite impulse response (FIR) and high-order ARX (auto-regressive with exogenous input) models remain popular in MPC applications, both of which can be identified with linear least squares methods. For the FIR structure, smoothing techniques are used to reduce parameter variance (e.g., Dayal and MacGregor (1996)). Model reduction techniques are typically used with high-order ARX models to reduce parameter variance (see, e.g., Zhu (1998)).

We have witnessed increased use of subspace identification methods in industrial MPC applications over the past 10 years. This follows the development of these algorithms in the 90's (Larimore, 1983; Larimore, 1990; Overschee and De Moor, 1994). A key advantage of a subspace method is that it directly yields a multivariable state space model, which is an advantage for a state-space controllers. However, even for FIR- or FSR-based MPC, a subspace method offers advantages as it considers the correlation of the output measurements in the identification, thus leading to a potentially more accurate and robust model. Industrial experience with a subspace identification method has been discussed in Zhao et al. (2006). Their experience has shown that complex relationships can be accurately modeled with a state space model of relatively modest order (range of 5 to 15), which captures both slow and fast dynamics. Advantages compared to a parametric technique are that the model order selection can be automated and only linear methods are required. Compared to FIR models, their experience has shown that subspace leads to more accurate estimates of gain and gain ratios, which are critical to capturing the true degrees of freedom in the MPC and ensuring reliable LP performance.

For the closed-loop situation, traditional subspace methods are biased; thus, special treatment is required. Modifications can be made to subspace methods that lead to consistent estimates (as summarized in (Qin, 2006)), although in theory, prediction error methods (e.g., ARX) lead to estimates with lower parameter variance. A challenge with closed-loop identification (using a direct approach) is the importance of obtaining an accurate noise model, which is problematic in practice, since typical process disturbances cannot be captured by white noise, passed thru a linear filter. In practice, one can attempt to minimize the bias by "overwhelming" noise feedback in the frequency range of interest (Jorgensen and Lee, 2002).

Important decision made during the model identification step relate to the following:

Data slicing Determining the sections of data should be included/excluded in the identification.

Data pre-processing Includes such option as spike removal, offset correction, prefiltering/detrending options, and shifting data based on known delays.

Selection of input and outputs – inputs include both candidate manipulated variables and measured disturbances.

Model Structure This includes decisions such as FIR model length, model orders of ARX or subspace, integrating variable or not

Nonlinearities Do nonlinearities warrant additional modeling?

Each of the above steps are typically iterative. With data slicing, the important issue is removing data that would otherwise lead to model bias. This includes time periods with significant unmeasured disturbances or plant upsets, such as pump shutdown, or where valve saturation occurs with PID loops. Prefiltering/detrending, can significantly impact the identification results. It is important to pre-filter/detrend to suppress slow drifts and minimize their contribution to model bias. In some MPC identification packages user options for prefiltering/detrending are not provided. Data differencing is often used, but since it suppresses low frequency information can lead to model gain errors.

In the selection of inputs and outputs, one will have a good idea of which are the manipulated and controlled variables, but it may not be as clear as to which other inputs should be selected as disturbance variables. Note it may be desirable to include a disturbance variable simply as part of the identification step to improve the quality of the models to the key manipulated variables, and not use it as a feedforward variable in the controller. With a subspace identification method, due to the fact that it explicitly considers the correlation of the outputs, the proper selection of output variables can improve the model accuracy of a given input-output channel, regardless of whether the additional outputs are used in the controller.

An aspect of model structure selection is whether to model a controlled variable as an integrating variable. Many times, process knowledge will guide this decision (such as liquid level to flow). However, slow responding stable variables (slower than the controller prediction horizon of the controller) often lead to improved control if modeled as an integrator, especially if they are subjected to input-type of disturbances.

Nonlinearities are typically handled with a static linearizing transformation on inputs and/or outputs. This is the familiar Hammerstein and Weiner model structures, as shown in Figure 6. In typical MPC practice, these static nonlinear functions are SISO (one-to-one) as opposed to MIMO. This is because a MIMO structure would be problematic when constraints are imposed. With physical insight, one may have knowledge as the functional forms such as valve-flow relationships or logarithm of distillation product impurity.


Figure 6. General Hammerstein-Wiener model structure; $f_H$ is the Hammerstein static nonlinear transformation, $f_W$ is the Weiner static nonlinear transformation.

For the general case, when a specific nonlinear transformation is unknown, a piece-wise linear relationship can be empirically derived, assuming testing is over a range wide enough to capture the nonlinearity. An example is shown in Figure 7 for the case of a valve position (controller output) and an associated measurement (e.g., flow). This transformation could be used with either of the valve position scenarios shown in Figure 4.

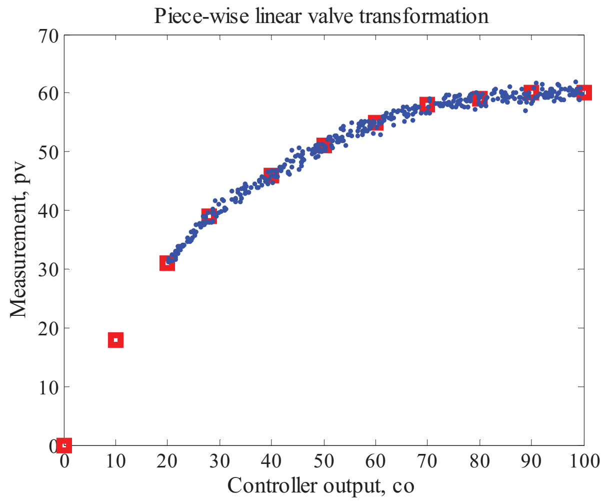


Figure 7.Example piece wise linear transformation

Many of the commercial MPC include the necessary pre- and post-processing capability to handle Hammerstein and Weiner transformations. To deal with dynamic nonlinearity one can use multiple models and "schedule" these based on knowledge of the operating point. Although this would be an easy thing to do, it is not commonly done with empirical models. An example of where multi models *are* routinely used is in ethylene applications, where there is a different furnace model for each major feed type.

**Inferential modeling.** For the situation where an inferential model must be developed for product qualities that are not measured online (measured infrequently by lab), a couple of approaches can be used.

The most common is to develop a regression model of the quality from directly measured variables such as flow, temperatures, and pressure. It is common for the multiple measurements (for example temperatures) used as inputs to the regression to be correlated. This requires multivariate regression techniques such as principal component regression (PCR), principal component analysis (PCA) and partial least squares (PLS). The key idea is to project the measurement values into a reduced number of important directions (number of directions less than the number of measurements) to avoid problems associated with correlation/ill-conditioning. Improved regression modeling is possible if a steady-state simulation model is available. In this case, measurements can be selected to minimize steady-state offset in the primary variables (lab measured) for expected disturbances and setpoint changes (Pannocchia and Brombilla, 2003; Hori et al., 2005).

The other approach to inferential modeling utilizes a simplified, fundamental (nonlinear) model of the processes, where parameters in the model are tuned (or optimized) to best fit the model to lab samples. In this case, the nonlinear model provides feedback to the MPC. The advantage of this approach (assuming the model is adequate) is that less process testing is required to fit the inferential model and the model can be expected to operate satisfactorily over a wider range of operation compared to a purely regression model. See, e.g., Friedman (2001), where a static nonlinear model is used for prediction of distillation product compositions.

## 4. CONTROLLER DEVELOPMENT

An MPC application is typically applied to a unit such as a fluid catalytic cracking unit (FCCU) or ethylene unit. A single MPC or multiple MPC controllers may be applied, depending on the unit objective and constraints. Consider as an example the FCCU shown in Figure 8. If the unit objective is to maximize unit feed and downstream throughput constraints exist, such as DC4 flooding, one would consider a single controller. If there are no throughput constraints in the downstream columns, one would consider two MPC controllers: one for the reactor/regenerator/ main fractionator/wet gas compressor, and one for the all of the downstream distillation columns.

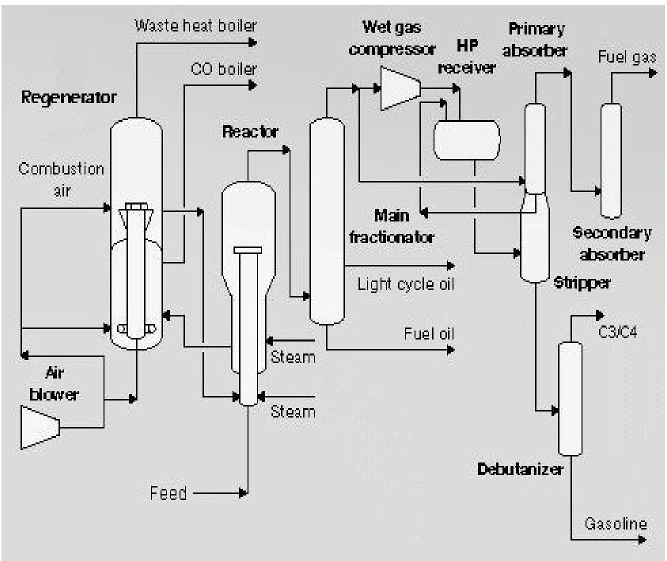


Figure 8. Fluid catalytic cracking unit.

A single unit controller is harder to implement and maintain, and if not implemented properly, or if sufficient engineering expertise is not available onsite, the result may be low MPC service factors or a controller that does not meet economic objectives. When a controller is not performing correctly or is not understood by operations, operators will typically “pinch” manipulated variables (set upper and lower limits close to each other) to overly constrain the MPC in order keep control within a region that the operator feels comfortable. When limited resources available are available, an alternative would be to first implement distributed controllers and later consolidate controllers after experience and confidence is gained.

It is good practice to develop models on an individual equipment basis. For example model reactors and distillation columns separately and build up the overall model from the various sub-models. Thus, the modeling should not be treated as one black-box, linking all inputs to all outputs (Haarsma and Mutha, 2006). If the modeling of the individual equipment is done properly, the key manipulated and controller variables have been identified and modeled and the manipulated variables for the overall model is the super set of MVs and CVs for the sub-models. Note that feedforward variables in the sub-models need to be truly independent variables from the viewpoint of the assembled model for the MPC.

With the above approach, it is typical to develop a sub-model based on its feed measurements (e.g., the feed rates to the primary absorber / stripper in Figure 8), but the overall MPC may require a model expressed in terms of unit feed. In this case, one can develop the required model from a convolution of the primary absorber sub-model and a model from unit feed to primary absorber feed. Note that the model prediction errors in the predicted feed to primary absorber feed can be used as a feedforward variable to the primary absorber / striper and DC4 with this arrangement. This is sometimes known as a prediction error feedforward in MPC jargon.

It is good modeling practice to ensure that the MPC model satisfy material balances (delta flows in equal delta flows out). When levels are controlled in MPC, the material balance consistency implies that the rate of change of levels *and* flows equal zero at steady state. Another area of consistency is where embedded PID loops imply a unity or zero gain.

As we have mentioned previously, the accuracy of the steady-state gains is critically important as they determine the steady-state operating point (target selection layer in Figure 2). This, in turn, can have a significant effect on the control layer as both target selection and dynamic control are executed at the same frequency. The challenge is that gains from an empirical model may not represent the true degrees of freedom that exist in the plant. As a result, the target selection layer may exploit fictitious degrees of freedom, a problem that tends to get .worse with problem size (due to the increased number of possible submatrices).

Consider the case that an LP is used as the target selection. At each execution , the LP will invert a square sub-matrix of the overall gain matrix. If the sub-matrix is ill-conditioned, the resulting changes to the plant may be excessive, possibly leading to cycling or instability. This normally becomes an issue when key manipulated variable handles are constrained (and therefore unavailable) and weaker manipulated variables must be used. Note that a degree of freedom can be removed from the LP by fixing gain ratios (forcing exact colinearity). A key modeling issues is deciding whether a degree of freedom exists or not. This decision can be guided by the models themselves and their uncertainty) or from engineering insight. Two approaches are used in practice to help with this problem. One approach is to analyze various sub-matrix combinations of the gain matrix in terms of singular value decomposition (SVD or the relative gain array. Sub-matrices with high condition number or large RGA elements become candidates for forcing a collinear relationship, particularly when expected gain errors suggest a co-linearity. Another approach is an online method that automatically disregards small singular values in the sub-matrix inverse, based on user defined tolerances (Qin and Badgwell, 2003). In the authors' opinion, neither approach is completely satisfactory. Analyzing sub-matrices can be a time consuming task and tuning with singular value tolerances can lead to unexpected effects.

During the controller development phase, initial controller tuning is performed. This relates to establishing criteria for utilizing available degrees of freedom and control variable priorities. In addition, initial tuning values are established for the dynamic control. Steady state responses corresponding to expected constraint scenarios are analyzed to determine if they behave as expected, especially with respect to the steady-state changes in the manipulated variables. This step may force additional analysis and treatment of gains and gain ratios.

## 5. COMMISSIONING

One reason we want to execute the various project steps well is to minimize rework in the commissioning phase. In the best case, commissioning of the controller involves simply making tuning adjustments and observation of the controller under different constraint situations and plant disturbances. In the worst case, control performance is unacceptable and the control engineer is forced to revisit earlier decisions such a base level regulatory strategy or plant model quality. Both of these can lead to retesting and re identification of at least portions of the plant model, resulting in delays and possible cost overruns.

During commissioning it is typical to revisit model decisions and assumptions, and switch out certain models, or modify gains, to obtain acceptable control. Typically, 50-70% of the commissioning effort deals with models.. Commissioning typically takes place over a 2-3 week period. In reality, commissioning is an ongoing effort, although the subsequent effort is normally treated as controller support and maintenance. During the commissioning phase there are only so many different constraint and operating scenarios that can be considered. Certain operating scenarios and constraint sets can *only* be observed certain times of the year due to seasonal effects. It is therefore important that the operating company have in-house expertise that can be used to answer questions ("whys is the controller doing that?"), troubleshoot, and resolve problems that arise over time.

Once a controller is commissioned, it is important to monitor controller performance to ensure benefits are maintained. Unfortunately, multiple factors can contribute to controller performance deterioration. A change in the operating point or a plant modification may invalidate portions of the plant model. Performance degradation of other control systems (PIDs and MPCs) can lead to poor performance. For example, a PID loop associated with, or upstream of, an MPC may develop a cycle resulting from valve stiction. While technology can help with the diagnosis, ultimately expertise must be brought to bear to resolve and correct the problem. Left uncorrected such problems lead to low service factors, or worse, an MPC being permanently switched off.

## 6. TRENDS AND SUGGESTED RESEARCH DIRECTIONS

The impact of faster and multi-core processors are being seen in MPC products. Increased processing speed is allowing an increased number of future moves to be calculated over the control horizon and also allows for much faster controller execution. In Barham (2006), an MPC approach is described in which all manipulated variables are valve positions. It is applied to an entire FCCU, and executes on a six-second interval. Transformations are used to linearize the relationship between valves and controlled variables. In Froisy (2006), a new state space controller is described that is based on an infinite horizon move plan, Notable features include model assembly of smaller submodels into one large overall MIMO state space model, and an automation feature that simplifies the configuration and tuning of disturbance estimators within a dynamic Kalman Filter framework. We are also seeing increased offerings of MPC at the DCS level where it can execute at a 1 second interval. However, unit wide or multi-unit MPC implementations are still most often implemented in a separate, dedicated computer.

In the remainder we provide suggestions for areas of improvement, including ideas for how this might be accomplished. General themes are of facilitating improvements at the various steps in an MPC implementation, maximizing the use of data and a priori knowledge, and minimizing the impact of changing or modifying key design decisions.

### *6.1 DCS Strategy*

As we have discussed, decisions related to structure selection of the combined MPC-DCS system are multifaceted. Fortunately, there is experience with many of the major refinery and chemical units that can guide these decisions, although specific experience may not always be sufficient for a particular plant (due to idiosyncrasies of the particular plant). This is of course problematic for processes or industries where MPC has not been previously applied. As a result, the path to an acceptable MPC controller may involve iteration. It is therefore advantageous if rework can be minimized in light of design changes. It is also clear that methods that rely on systematic design rather than trial and error only would be valuable.

In recent years, techniques and products have been developed which apply multivariable identification methods to develop models that are in turn used to tune PID loops. Such approaches can be used to improve the performance of PID loops associated with an MPC system with reduced engineering effort (Zhu, 2003; Harmse et al., 2009). Note that once a multivariable model is available (relating the effect of PID controller outputs on PID controlled variables), one could use standard techniques such as relative gain array (RGA) or block relative gain (BRG) (as a function of frequency) to focus on the most promising PID loop pairings and simulate various suggested pairing possibilities. Experience has shown that testing and developing a multivariable model for the typical loops found at the DCS level can often be completed within a day for the typical loops that are found at the DCS level (Darby and Harmse, 2009).

Changing the PID loop pairings or tuning parameters (if behavior is significantly different) requires a change to the affected models in an MPC system. Historically, such changes have required plant retesting. However, with completed knowledge of the models at the PID level (including the PID controllers themselves), it is theoretically possible to convert the MPC models to reflect a different PID configuration or tuning), potentially avoiding an expensive retest. Such an approach is described in Rejek et al. (2004). One major claim for this approach is that one could perform the plant test in one DCS configuration, but implement the MPC in another configuration as in Barham et al. (2006). To our knowledge, various options for solving this problem have not been investigated. Open questions concern accuracy and robustness issues as to how best to perform this model conversion.

*6.2 Plant Testing*

It is well known that that independent binary input test signals are generally inadequate (inefficient at best) for the identification of ill-conditioned systems. The reason is that the weak process directions (e.g., separation changes in a distillation column) are poorly identified in the presence of noise. The solution is to use correlated inputs, which can be generated in open or closed loop (Anderson and Kummel, 1992; Koung and MacGregor, 1994; Li and Lee, 1996). For example, in a distillation column, large changes in both reflux and reboil flow rates are required to adjust separation in any significant way. As discussed previously, ill-conditioning is often found in the MPC steady-state gain matrix. Properly designed input sequences can be expected to improve estimation of ill-conditioned sub-matrices. Recent results show that independent binary signals can also be inferior for well-conditioned systems, depending on the active constraints. In Darby and Nikolaou (2008a, b), using a criterion which maximizes the likelihood of satisfying integral controllability, optimal inputs (both amplitudes and covariance of the inputs) are shown to depend on both the system's conditioning and the specific active constraints. While correlated inputs can be achieved with independent perturbations of controller CV setpoints or limits, such an approach may translate into ineffective input perturbations due to the influence of the target selection layer. A closed-loop experimental design approach for MPC would be desirable, although treated rigorously, would require knowledge of the feedback law. This would be problematic for MPC as each constraint set represents a different control law. A possible approach is to replace the binary test signals that are currently used in closed-loop MPC with a traditional or control-relevant experimental design. An experimental design could be performed consistent within a feasible region established for the target selection layer and implemented through the controller to ensure constraint satisfaction. This might be done in a manner similar to that used in Sagias (2004) for PRBS signals, where the dynamic objective function is modified to the allow trade-off of control and test objectives. The other aspect of experimental design concerns frequency content. This aspect would need to be investigated as well. We note that with current MPC practice, the frequency content is specified indirectly based on the type of binary signal chosen and the specified average pulse width. Extending this concept further, if basis functions with desired frequency content were pre-specified, this might allow the experimental design to be expressed in terms of input amplitudes and covariances.

*6.3 Identification*

As mentioned earlier, there are multiple consistency relationships (e.g. gains and gain ratios) that should be enforced in the constructed MPC model. Instead of imposing these conditions by altering the identified model as a post-processing step, it would be better to incorporate these as constraints in the identification. Within the context of least squares, imposition of linear constraints results in parameter estimators with smaller variance (Seber and Lee, 2003).

Other consistency relationships could be incorporated. Material balance consistency has been discussed, but consistency can be extended to component balances. For example, for binary distillation columns, relationships can be derived which link the steady-state gains associated with top and bottom purities for a given regulatory control structure (Häggbloom and Waller, 1988).

Another area that should be exploited is a priori information available in the form of physical models. Such an approach was discussed for a steady-state inferential predictor. The basic idea is to combine available model information and data in a grey-box identification problem. The key motivation is one of getting better models with less data and effort, not necessarily one of capturing the nonlinear behavior. A linearized model from a fitted nonlinear model may well be adequate. However, it the nonlinearity were significant, the nonlinear model could be used to update models in the MPC. We should mention that in our view (for the foreseeable future) a full nonlinear model is not needed or feasible for the majority of control problems common found in industry (polymer applications and batch applications being notable exceptions). Tools to empirically determine the Hammerstein and Wiener static compensators would be useful (such as described in Zhu (2000) for the case of cubic splines). One could also consider combing the dynamic identification step with piece-wise linear transformations in a single identification problem. We might expect that nonlinear models could be developed for certain submodels of an MPC, if the improvements or costs saving to develop the model are significant. The online implementation might be posed as a constrained estimation problems using techniques such as found in Rawlings and Bakshi (2006), where the estimator would provide feedback (and possibly future predictions) to MPC. An example of a common situation where nonlinear affects are often encountered is variable liquid hold-up (e.g., reflux accumulator), which causes a variable dynamic response in downstream composition signals.

*6.3 Improved Disturbance Estimators*

A key advantage in utilizing a general state space formulation is improved (unmeasured) disturbance modeling. For example, it is well known that the output bias approach, traditionally used for the MPC model update step, can lead to sluggish response to an input disturbance (Shinskey, 1994). A properly designed estimator overcomes this limitation (Muske and Badgwell, 2002; Pannocchia and Rawlings, 2003). An additional advantage of state space disturbance model is that of incorporating additional output measurements. A typical example is shown in Figure 9. The variable $u$ represents the MPC manipulated variable and y is the MPC controller variable; yI is an intermediate variable. Examples include:

Case 1: $u$ is plant feed rate, $y_I$ a downstream flow measurement and $y$ is a downstream controlled variable.

Case 2: $u$ is column reflux flow rate, $y_I$ a tray temperature, and $y$ a product analyzer.

Case 3: $u$ is a PID setpoint, $y_I$ is the PID error and, $y$ is an MPC controlled variable..

Case 1 represents the example considered earlier (cf section 6). Case 2 provides structure similar to a traditional cascade control (Froisy, 2006). Case 3 models the behavior of the base level PID, e.g., a time series model of the PID error, which has the advantage that unnecessary moves are not generated by MPC when the base layer is capable of rejecting the unmeasured disturbance (Haarsma and Mutha, 2006). Improved disturbance modeling could also be applied to the situation where MPC is directly manipulating a valve (and local flow, temperature, and/or pressure measurements are available).

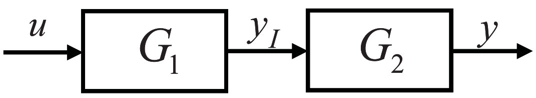


Figure 9. Plant model with intermediate variable $y_I$.

While it is possible to replicate such approaches within traditional FIR- and FSR-based MPC, they involve ad-hoc solutions. An interesting possibility is the use of improved disturbance estimators within traditional FIR- or FSR-based MPC (Badgwell, 2009). What is unclear is the extent to which these improved estimators are actually being used within existing state space controllers. Anecdotal evidence suggests a gap between these capabilities and actual usage by MPC engineers. Part of the challenge in developing these more general estimators is that it requires linking disturbances to particular model channels. Tools and techniques to facilitate or simplify this step would be helpful.

*6.4 Robustness*

Model errors impact performance of MPC at both the target selection layer and the dynamic controller, although, as we have seen, the problem is more acute with the steady-state target selection layer. While the target selection layer offers advantages in terms of constraint control, economic optimization, and dealing with non-square systems, it represents a source of challenges for an MPC implementation, ones that grow with the size of the controller. The goal is to prevent the optimizer from exploiting fictitious degrees of freedom, and from exploiting true degrees of freedom that may exist, but lead to large steady-state moves for only small economic improvement. Another challenge is minimizing the impact of effects that can lead to chatter in the steady-state targets (Shah et al., 2001; Kozub, 2002). This includes high frequency noise associated with controlled variables, unmeasured disturbances and/or model error. An approach that has been used industrially to minimize change from the optimizer layer to the dynamic layer is based on a minimum-movement criterion (to achieve all control objectives) in the dynamic layer and to invoke a QP optimization once all predicted controlled variables are within a pre-defined funnel (Lu, 2003).

Given the importance of the steady-state gain matrix in the optimizer, Kassman et al. (2000) proposed a robust LP formulation based on ellipsoidal uncertainty of the gain matrix. An advantage of their approach is that the resulting optimization problem is convex. An open question is how well their approach addresses problems with ill-conditioning. Note that we have avoided mentioning worse case formulations due to their tendency to provide overly cautious control for the average case.

The challenges outlined above could benefit from additional research. Pertinent questions are whether it is possible to avoid inverting the gain matrix for the entire plant and whether techniques could be used to avoid exploiting uncertain (and undesirable) degrees of freedom. These issues might be considered with the general problem of how to coordinate multiple MPCs, which is currently receiving increased research attention. .We note that when the plant optimum is consistent with maximum throughput, a simplified coordinator can be used (Aske et al., 2008). Such an approach explicitly limits the degree of freedom that are used in the plant wide control scheme.

## 7. CONCLUSION

The MPC algorithm is a mature technology and there is good understanding of the algorithm's properties and behavior. But as discussed, there are facets of the technology that could be improved. As one would expect, the performance of MPC systems does not depend only on the "control law" (MPC tuning) but on successful completion of all of the following steps: articulation of control objectives, selection of measurements and manipulations, configuration of controller structure (i.e. interconnections among MVs and CVs), and, finally, design of the control law (Stephanopoulos, 1984). Even though the control law can be designed in a fairly systematic way, completion of the design steps above it is less systematic, and offers a margin of creativity. Process understanding remains indispensable for these steps. Improving the ability to systematically complete these steps would certainly contribute towards designing better MPC systems. Industry and academia can continue collaboration towards this end, with full understanding of the need for sanitized academic solutions to bear industrial relevance and that common practice may not necessarily be best practice.

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