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MPC: Current practice and challenges

Mark L. Darby [a,*], Michael Nikolaou [b]

[a] CMiD Solutions, 13106 Dogwood Blossom Trail, Houston, TX, USA
[b] Chemical and Biomolecular Engineering, University of Houston, 4800 Calhoun Ave. Houston, TX 77204-4004, USA

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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 control problem. This includes the design of the underlying regulatory controls, design of the MPC(s), test design for model identification, model development, and dealing with nonlinearities. Approaches and techniques that are successfully applied in practice are described, including the challenges involved in ensuring a successful MPC application. Academic contributions are highlighted and suggestions provided for improving MPC.

1. Introduction

Model predictive control (MPC) is a mature technology and has become the standard approach for implementing constrained, multivariable control in the process industries today. MPC provides an integrated solution for controlling systems with interacting variables, 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, MVs) than outputs (controlled variables, CVs), 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, typically non-square, to predict the future response of the controlled plant and take appropriate action through optimization. While the model may be linear or nonlinear, linear MPC is considered here, as it is used in the majority of industrial applications in the refining and petrochemical industries today (and increasingly, in other industries). For these applications, the plant model is identified using 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 have seen significant efforts by technology suppliers to improve the usability of their MPC products.

While the “science” of MPC has advanced and the technology is now easier to apply, there is still a significant “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 in the course of an implementation. In addition, there are both technical and organizational issues that are critical to ensure that MPC benefits are sustained in the longer term once an MPC is commissioned (Darby & Teeter, 2005). 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, the main emphasis concerns the technical aspects of MPC that arise in the course of a project implementation.

MPC is positioned above the regulatory control level in a cascade arrangement as shown in Fig. 1. The manipulated variables for the MPC are typically setpoints of underlying PID controllers, executed in a distributed control system (DCS). The MPC may also directly manipulate valve position signals rather than PID setpoints. Being below the MPC level in the multi-level plant hierarchy, the DCS executes a at a higher sampling rate than the MPC, typically sub-second to multi-second sampling period, compared to (typically) a 30 second to 2 minute execution period for the MPC.

Some targets are local to the MPC. Other targets come from planning and scheduling, which are communicated to the operator in an open-loop fashion. A subset of the targets may come 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, and they will change over time based on economics and priorities. 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-to-day logistical issues that impact the targeting of an MPC, such as a late shipment or a product tank becoming full.

Critical to successful implementation of MPC is the configuration of the DCS regulatory controls, which includes the following:

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* Corresponding author. Tel.: +1 281 477 7791; fax: +1 281 469 244.
E-mail addresses: darbymark@sbcglobal.net (M.L. Darby), nikolaou@uh.edu (M. Nikolaou).

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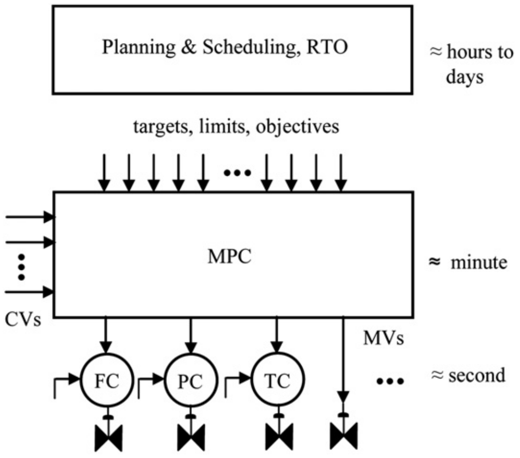

Fig. 1. Plant control hierarchy.

PID loop pairings, use of cascades and/or ratios, and whether it is more appropriate for the MPC to directly manipulate valve positions. An existing regulatory control strategy should not be simply taken as a given. The plant control design problem is one of deciding on the best overall structure for the regulatory level *and* MPC, given the control objectives, expected constraints, qualitative knowledge (at least) of the expected disturbances, and robustness considerations. These design decisions have a far bigger impact on the success of an MPC project than the performance of the MPC algorithm itself (Vogel & Downs, 2002). The selection of the controlled variables for MPC is not one of simply deciding which subset of available measurements should be selected. It may well 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, the problem of inferring qualities from secondary measurements arises. 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; Foss, 1973; Larsson & Skogestad, 2000; Lee & Weekman, 1976; Morari, Arkun, & Stephanopoulos, 1980; Weber & Brosilow, 1972).

Once the regulatory level configuration has been decided, 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-linearity is an issue 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 algorithm.

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 plant instrumentation is adequate. It is common to retune a significant number of PID loops, with significant benefits often resulting from this step alone. The tuning emphasis is on disturbance rejection, but standard DCS options are used to also ensure satisfactory setpoint response. An outcome of this phase is a list of issues that must be 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 constraints. In addition, a preliminary design for the MPC is typically performed, i.e., selection of controlled and manipulated variables, and number of MPCs.

In plant testing, the process is excited by changing expected independent variables of the MPC to generate 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. Also during this phase, frequent lab measurements are collected, if an inferential model of product qualities is required.

In the next phase of work, modeling of the plant is performed, including any required inferential calculations and non-linear compensators (usually static). It is here that the models are analyzed for consistency, including, for example, insuring that steady-state model gains are consistent with physical and process knowledge. The final design for the controller(s) is completed and simulations performed to test the model and tune the controller.

Commissioning involves observing and testing the performance of the MPC controller on the plant. Tuning adjustments and model changes are made as required to obtain a controller that performs well for the typical disturbances and constraint sets that will be encountered. Training of operations staff on the live controller is begun in this phase.

In the following, a high level description of MPC is provided without emphasis on the particular theoretical properties of the MPC algorithm, of which there is already a substantial body of work (Mayne, Rawlings, Rao, & Scokaert, 2000). This is followed by a detailed discussion of the key tasks and decisions that are made in the course of an MPC implementation. Current practice is highlighted and guidelines are given. The impact and suitability of MPC outside traditional industries is then considered. Finally, academic contributions are highlighted and suggestions provided for how MPC can be improved.

2. MPC overview

A simplified block diagram of the typical MPC is shown in Fig. 2. Key functionalities of the components shown in the figure are described below.

Target Selection: Target selection determines the best feasible, steady-state operating point for controlled outputs and manipulated inputs, $\mathbf{y}_k^s, \mathbf{u}_k^s$, respectively, 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).

Controller: The controller determines optimal, feasible future inputs over a moving horizon to minimize predicted future controlled errors of controlled outputs from targets determined

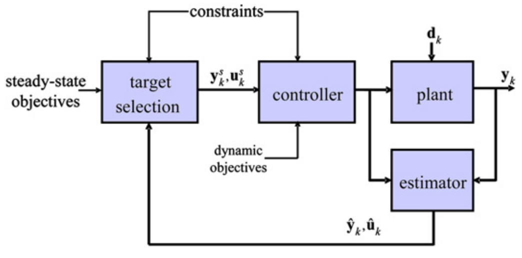

Fig. 2. Simplified MPC block diagram.