Application of Model Predictive Control Methods in the Process Industries

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***Abstract*— Model Predictive Control (MPC) technology is widely used in the process industries to solve challenging multivariable constrained control problems and to achieve economically optimal operation of continuous process plants. This paper explains reasons for the industrial success of MPC and describes the functionality of commercially available MPC packages. Finally, current trends and developments of industrial MPC application are discussed.**

***Keywords*— advanced process control; model predictive control; system identification; multivariable control; steady-state optimization; operational excellence**

I. Introduction

Model Predictive Control (MPC) continues to be the technology of choice for constrained, multivariable control applications in the process industries, in particular for continuously operated plants. No other advanced control technology has achieved a bigger impact on modern process control and represents such an industrial success story. Nowadays, more than 15.000 MPC applications are running not only in the refining/petrochemical industry, but also in polymer and chemical, pulp and paper, cement, food and power industry [1, 2]. The vast majority of industrial MPC applications are based on linear process models developed from active plant tests and system identification. These controllers are also called LMPC.

According to several international studies, the Advanced Process Control (APC) economic benefits are in the range of 1…5% throughput increase, 2…10% yield increase, 3…10% energy consumption reduction, and 20…50% time reduction in grade changes. Return on investment can be achieved in 3…6 months (refining) up to 2 years (chemistry). Therefore, MPC techno-logy based APC projects are treated as attractive option for cost-effective plant operation and included in companies operational excellence programs [3].

Fig. 1 shows how MPC is embedded in the control hierarchy of large process plants. MPC controller inputs are control and (measurable) disturbance variables (CVs and DVs) provided by measurement devices and virtual online analyzers (softsensors). MPC controller outputs (manipulated variables, MVs) in most cases act as setpoints on underlying PID controllers which already exist on the distributed control system (DCS). MPC control algorithms are usually implemented on dedicated computers connected to the DCS via OPC interface. Sometimes, MPC have interfaces to higher level applications such as Manufacturing Execution and Enterprise Resource Planning Systems (MES/ERP), coordination of several MPC controllers in large plants, or Real Time Optimization (RTO) systems.

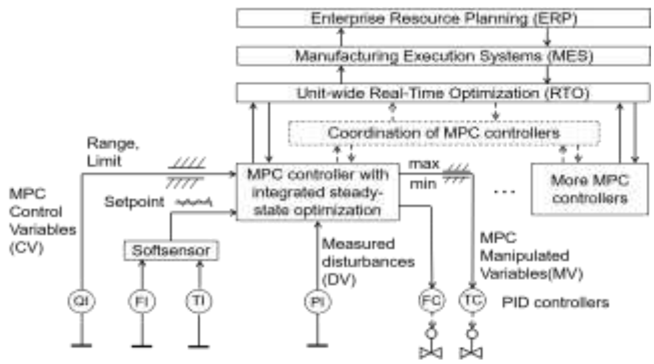

Fig. 1. MPC in the control hierarchy of process plants

The paper is structured as follows. In section II, the basic setup and the "ingredients" of MPC are shortly described. Section III summarizes reasons for the industrial success of MPC. Section IV gives an overview of MPC project steps and software. Finally, Section V discusses some of the current trends in MPC development and application.

II. Basic Setup of Model Predictive Control

A simplified MPC block diagram is presented in Fig. 2.

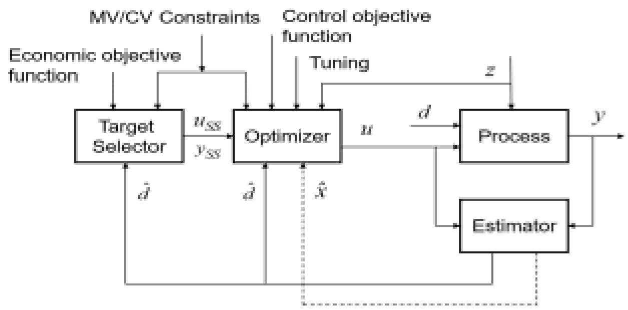

Fig. 2. Simplified MPC block diagram

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The "Target Selector" determines the best feasible steady-state operating point for controlled and manipulated variables y_{SS} and u_{SS} based on steady-state gains of the process model, solving a linear optimization (LP) problem with an *economic* objective function $J_{SS} = c^T u_{SS} + d^T y_{SS}$. The "Optimizer" determines optimal, feasible future manipulated variable moves over a control horizon n_C to minimize future control errors of controlled variables from the targets calculated before. This is done by solving a dynamic quadratic optimization (QP) problem with a *control-oriented* objective function $J(k) = \|w(k) - \hat{y}(k)\|_Q^2 + \|\Delta u(k)\|_R^2$; the future control errors are predicted over a prediction horizon n_P, based on a dynamic process model processing manipulated variables u and measured disturbances z. Various model forms are used in practice. Most common are still finite step response models. Some commercial MPC controllers also use state-space models which are more flexible in modelling unmeasured disturbances in the estimator, and are suited for unstable processes as well. The "Estimator" updates the model predictions to account for unmeasured disturbances and model errors. In its simplest form, the current offset between the control variable measurements and their predictions is used to bias future model predictions. This corresponds to an output step-like disturbance model. For other disturbance models, although more expensive, state-space descriptions and Kalman filtering are better options for estimation and improve the overall controller performance. If state-space models are used for prediction, state estimation $\hat{x}$ is usually necessary and can be performed in conjunction with disturbance estimation $\hat{d}$.

The steady-state and dynamic optimization problems described above consider inequality constraints for both manipulated variables (absolute and rate-of-change constraints) and control variables (range or zone control):

$$\left.\begin{aligned} u_{\min}(k) \le u(k+j) \le u_{\max}(k) \\ \Delta u_{\min}(k) \le \Delta u(k+j) \le \Delta u_{\max}(k) \end{aligned}\right\} j = 0, 1, \ldots n_C - 1$$
$$y_{\min}(k) \le y(k+j) \le y_{\max}(k) \qquad j = 1, 2, \ldots n_P$$

This is also shown in Fig. 3 which illustrates the MPC scenario in the single-input, single-output case.

Detailed mathematical descriptions of prediction, optimization and estimation tasks to be solved following the receding horizon principle can be found in several textbooks, e.g. [4, 5, 6].

III. Industrial Success of MPC

There are several reasons for the remarkable industrial success of MPC applications.

Industrial process units and plants are *multivariable* in nature, i.e. characterized by interactions between the manipulated and controlled variables. On the other hand, MPC algorithms can easily be extended to the multivariable case. In commercial MPC packages, the number of MVs, CVs and DVs is freely configurable by the user. MPC controllers in refining processes typically include 10…20 CVs and 20…40 MV/DVs.

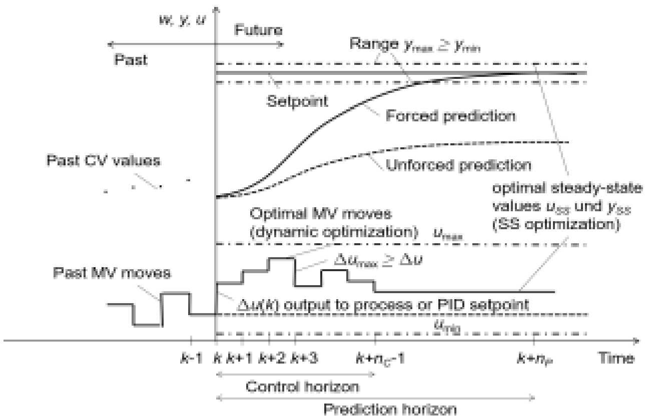

Fig. 3. MPC basic setup

In process operation, MV are *constrained*, i.e. the can only be changed within limits and with a certain velocity. Process operation itself is exposed to constraints: examples are limited cooling, heating or vacuum capacities, as well as material-related temperature constraints in chemical reactors or flooding constraints in distillation towers. For some CVs, it is more appropriate to specify limits or ranges (inequality constraints) than setpoints (equality constraints). The optimal operating regime of process plants lies often at the intersection of those constraints. The biggest single advantage of MPC algorithms is their ability to deal with such constraints in an explicit, systematic manner by solving constrained optimization problems in real-time.

Under industrial conditions, malfunctions of sensors or actuators cannot be completely avoided. Process upsets may require operator intervention including switching PID controllers – which are normally manipulated by the MPC controller – into manual mode. On the other hand, MPC controllers CVs must not be taken into account unless they violate their limits. As a consequence, the number of available MVs, and CVs to be considered may change during online operation. MPC algorithms automatically recognize the actual structure of the control problem and find the best possible solution for the current situation. Fortunately, this does not require MPC controller reconfiguration or retuning.

The optimal operating point of a process plants varies with its technical and economic conditions (different feed and energy sources and prices, changing production demand etc.). The MPC *integrated steady-state optimization* function allows to automatically determine this optimal operating point and pass it to the dynamic part of the controller. Therefore, commercial MPC packages are not just multivariable regulatory controllers, but also economic optimizers, at least for that part of the plant which is comprised by the MPC controllers' MVs/DVs/CVs.

In contrast to other modern control algorithms, MPC (with some training) is easily understood and operated by non-experts in the field of control theory. Mature and reliable software, experienced APC engineering companies, a standardized project flow and cost reduction due to better modelling tools, standardized interfaces and browser-based visualization break down hurdles for increased MPC utilization in industry.

IV. Project steps and MPC software

The typical sequence of steps for advanced control projects including MPC technology application is as follows:

A *functional design and benefits study* is carried out first, proving improvements in process operation and calculating achievable economic benefits. A preliminary MPC design is performed, i.e. the MV/CV/DV structure and the number of MPCs are selected.

In the *pretest* phase preliminary information about process dynamics, operation and constraints is collected, and instrumentation is checked and eventually fixed. In many cases, underlying PID controllers are retuned and advanced regulatory controls are reviewed and sometimes modified. Significant benefits usually result from this step alone.

The most important and time-consuming project phase is *plant testing*, where expected independent variables are changed to generate data for model identification. Testing may be performed manually or automatically. Frequent lab measurements are collected, if an inferential model of product qualities is required.

System identification software (usually part of the MPC package) is used for plant dynamics modelling, including inferential calculations (or softsensors). It is particular important to assure that steady-state gains of the models are consistent with physical and process knowledge.

The final *design* of the MPC(s) is completed and off-line simulations are executed for preliminary controller tuning. Typical scenarios are tested which are expected to occur in the later industrial setting (for example different constraint scenarios, sensor/actuator malfunction etc.).

MPC(s) are implemented on the target hardware, and commissioning of the controller begins with testing the OPC interface and the operator screens. *Commissioning* also involves observing MPC performance in the plant under typical disturbances and constraints, and potential model changes and tuning adjustments. Training of operators on the live controller is begun increasing gradually their responsibility and independence.

The project is usually finished by providing a detailed *documentation and training* for different staff members. APC project results are financially assessed. To ensure long-term sustainability of MPC solutions, a program of systematic maintenance must be established aimed at the detection and correction of performance degradation.

At the beginning of application in industry, MPC software was little more than the MPC code itself completed by a dedicated computer/DCS interface. This has dramatically changed over the last two decades: commercial MPC packages (see a list of selected commercial MPC packages in Table I) nowadays include tools for automatic plant testing and sophisticated model identification methods, MPC/DCS communication via standardized (OPC) interface, browser-based operator screen designs MPC performance monitoring, and eventually interfaces to MPC coordination and RTO applications. This toolset allows to substantially reduce project costs and is one of the reasons for increasing number of MPC applications in non-traditional branches of industry. Table I lists selected commercial MPC packages.

TABLE I. Selected MPC packages

Vendor	MPC package
Aspen Technology	DMCplus, DMC3
Honeywell	Profit Controller
Rockwell Software	Pavilion8
IPCOS	INCA MPC
Shell Global Solutions	SMOC

Some larger companies use in-house developed MPC, for example Statoil (SEPTIC) and Petrobras (SICON). The MPC Toolbox of Matlab/Simulink is an excellent tool for education, but not suited for use in industrial process control.

V. Trends of MPC development

Although MPC using linear models has already reached a quite mature state, there is still room for improvement. The following paragraphs give a short overview on recent developments.

1) In the majority of cases, dynamic process models for MPC controllers are developed based on plant tests and system identification from measured data. Traditionally, a sequential approach for plant tests is used, i.e. a series of step tests is executed MV by MV. For slow process dynamics and a bigger number of MVs, this leads to substantial test durations and increased project costs. Therefore, recent MPC packages allow simultaneous test signal (PRBS) generation and include multivariable system identification concepts. In addition, online identification methods are used, where new models can be identified when the MPC controller is running in automatic mode. Further developments are aimed at an automatic identification/re-identification of the process dynamics: tools like Aspen SmartStep and Honeywell ProfitStepper and TaiJi Online are examples for that [7, 8]. Another direction is the use of subspace identification techniques for linear state-space model identification which allows to take advantage of this model class within MPC.

2) The majority of commercially available MPC packages is installed on a dedicated computer and communicate with the Distributed Control System via OPC. This allows to connect different MPC packages with any DCS. Some DCS vendors have recently integrated MPC algorithms in their process stations themselves. This enables cost-effective engineering and easier online deployment. Examples are the Honeywell Experion Profit Controller, Emerson’s DeltaV Predict/ PredictPro MPC, or Siemens PCS7 ModPreCon function block.

3) During the last two decades, methods and tools have been developed for Control Performance Monitoring (CPM) of the basic regulatory (PID) control system. They support the systematic supervision and assessment of PID controllers and assist in diagnosing causes for poor controller performance. Although CPM theory for MPC controlled systems is still under development, commercial packages already include

CPM metrics to assess MPC control performance. For example, plant-model-mismatch and the potential need for re-identification of some of the sub-models can be detected. Aspen Watch and Honeywell Profit Expert are CPM tools for their related MPC controllers, but independent CPM software is also available, e.g. Metso Expertune PlantTriage. These tools contribute to pro-active maintenance of MPC applications and are aimed at increasing their sustainability under changing operating conditions.

4) MPC offline design tools include a process simulator to allow closed-loop control system simulation, tuning and test of different scenarios before implementing the online controller on the target hardware. This process simulator usually replicates the process model used within the controller itself, i.e. no plant-model mismatch is assumed. Of course, the simulation model can intentionally be modified to introduce some deviation between the MPC internal model and the simulated plant behavior. But, a much better approach for conducting robustness studies is to integrate the MPC controller with an independent dynamic simulation package or an operator training system (OTS) in case such a system has already been developed. Since those simulators are based on nonlinear rigorous models, much more realistic robustness studies can be performed. In addition, OTS can also be used to execute virtual plant tests (at least partly instead of real tests) and therefore, further reduce the effort for MPC model development. Finally, rigorous dynamic simulators can also be used to provide and transfer actual gain information for MPC, thus allowing online gain adaptation.

5) As stated above, the vast majority of industrial MPC applications are based on linear, time-invariant process models. Successful application presumes mild nonlinearities, operation in a narrow band around the operating point and constant static and dynamic plant behavior. While these conditions are met in many refinery and petrochemical processes, there are a lot of applications where this is not the case. Examples are polymer plants with grade switches (changing density and melt index specifications), batch processes or power plants with frequent load changes. Therefore, several approaches have been developed to apply MPC technology to these processes as well. Traditional methods for this purpose are LPMC enhancements such as nonlinear variable transformations, providing information about gain/delay changes online, multiple model approaches, and linearization of rigorous models along pre-optimized trajectories. But during the last decade, substantial improvements have been achieved in nonlinear model predictive control (NMPC). Here, an empirical or rigorous nonlinear process model is used within the controller. That sounds conceptually simple, but raises difficult problems ranging from nonlinear system identification, repeated nonlinear constrained optimization in real-time, nonlinear state estimation, and last but not least nonlinear model development and maintenance [9]. Therefore, it is no wonder that industrial NMPC applications are still rare and limited to some types of process plants.

A promising but even more challenging development is “Economic Model Predictive Control” (EMPC). As depicted in Fig. 4, the traditional two-level structure of steady-state economic optimization and dynamic regulation (RTO/MPC) is given up in favor of an integrated concept.

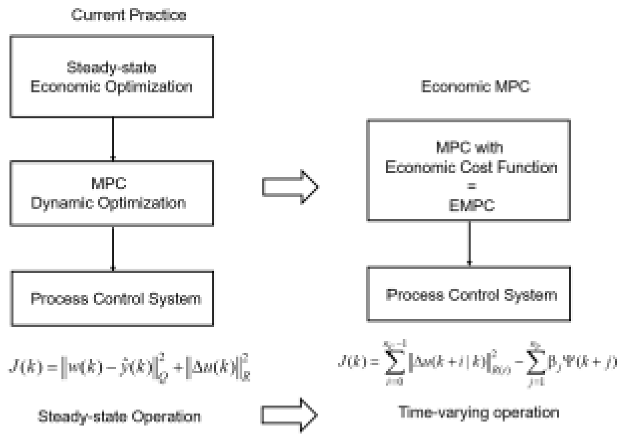

Fig. 4. Two-level RTO/MPC vs. EMPC structure

A rigorous nonlinear process model is used, and the two different objective functions for economic optimization (target calculation) and dynamic target tracking are combined in a single objective function. Steady-state optimization is replaced by dynamic optimization of the operating cost of the process [10, 11]. Admittedly, this concept requires not only a substantial modelling effort, but also the existence of sophisticated software and IT infrastructure for all parts of application development, and finally qualified personnel for control system design, commissioning and maintenance. An impression of what can be achieved and which challenges have to be mastered, the reader can get from pilot applications [12].

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