
Integration of Advanced Model Based Control with Industrial IT

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Summary. Advanced model based control is a promising technology that can improve the productivity of industrial processes. In order to find its way into regular applications, advanced control must be integrated with the industrial control systems. Modern control systems, on the other hand, need to extend the reach of traditional automation systems – beyond control of the process – to also cover the increasing amount of information technology (IT) required to successfully operate industrial processes in today's business markets. The Industrial IT System 800xA from ABB provides a scalable solution that spans and integrates loop, unit, area, plant, and interplant controls.

This paper introduces the 800xA and the underlying Aspect Object technology. It is shown how model knowledge and optimization solver technology are integrated into the 800xA framework. This way, advanced model based control solutions can be set up in an open and modularly structured way. New model and solver aspects can be combined with available aspects covering standard functionality like process connectivity, management of process data, trend&history data and application data, as well as operator graphics.

A Nonlinear Model-based Predictive Controller (NMPC) for power plant start-up is treated as example. This paper discusses how NMPC can be integrated with a modern control system so that standard concepts are re-used for this advanced model based control concept.

1 Introduction

During the last decades, several advanced control technologies have been developed, including adaptive control, fuzzy control and neuro control. While each of these technologies offers advantages over classical control methods, PID controllers still dominate the vast majority of industrial applications.

One reason for the lack of mainstream use of advanced control technologies is seen in the fact that they require specialized engineering knowledge and tools. Normally, specialized experts are required to apply advanced control methods. A better integration of advanced control technologies with regular control systems is seen as a key factor for improved acceptance.

Nonlinear model based control (NMPC) has received much attention during the last years. The technology has several advantages from a control point of view: it accommodates nonlinear, multi-variable problems with state constraints.

Important achievements have been made to treat the computationally challenging task of formulating and solving large-scale nonlinear optimization problems on-line [2, 4, 6]. Moreover, NMPC has the advantage that the technology is more open, compared to other advanced control methods. Models do represent the behavior of a plant and standard optimization algorithms are used to apply the models to control. This openness improves the acceptance of NMPC on the one hand side.

On the other side, still special purpose tools are required to implement model based control. This implies that concepts which are readily available in a standard control system need to be specifically interfaced or even redeveloped for applications of model based control, including e.g. signal exchange with sensors, actuators and low level controls, operator graphics, trend&history display, signaling of alarms and events, as well as system maintenance. This is seen as an important burden for both: acceptance and cost of NMPC.

2 The Industrial IT System 800xA

2.1 System Overview

The Industrial IT System 800xA seamlessly integrates traditionally isolated plant devices and systems, extending the reach of the automation system to all plant areas. The result is a simplified, software representation of the plant, from simple on/off-type switches and valves to smart field devices, dedicated control subsystems, and PC-based supervisory systems [1].

The framework for the 800xA system architecture is built upon ABB's Aspect Object technology. Aspect Objects relate plant data and functions – the aspects, to specific plant assets – the objects. Aspect objects represent real objects, such as process units, devices and controllers. Aspects are informational items, such as I/O definitions, engineering drawings, process graphics, reports and trends that are assigned to the objects in the system.

Aspect Objects are organized in hierarchical structures that represent different views of the plant. One object may be placed multiple times in different structures. Examples for different types of structures are:

Functional Structure: Shows the plant from the process point of view.

Location Structure: Shows the physical layout of what equipment is located where in the plant.

Control Structure: Shows the control network in terms of networks, nodes, fieldbuses, and stations.

The idea of placing the same object in multiple structures is based on the IEC standard 1346 [3, 9].

The Plant Explorer is the main tool used to create, delete, and organize Aspect Objects and aspects. It is based on a structural hierarchy, similar to Windows Explorer, as demonstrated in Figure 1. The object hierarchy is visible on the left hand side of the window. The upper right pane shows the aspects of an object and the lower right pane views a selected aspect.

2.2 Integration of Model Based Control

A new Model aspect has been developed so that mathematical model information can be added to an Aspect Object. The model has the form of a hybrid differential algebraic equation system (hybrid DAE)

$$\mathbf{0} = \mathbf{F}[\mathbf{x}(t), \dot{\mathbf{x}}(t), \mathbf{m}(t), \mathbf{u}(t), \mathbf{z}(t), \mathbf{y}(t), \mathbf{p}, t], \quad (1)$$

$$\mathbf{F} : \mathbb{R}^{n_x} \times \mathbb{R}^{n_x} \times \mathbb{R}^{n_m} \times \mathbb{R}^{n_u} \times \mathbb{R}^{n_z} \times \mathbb{R}^{n_y} \times \mathbb{R}^{n_p} \times \mathbb{R}^1 \mapsto \mathbb{R}^{n_x}$$

$$\mathbf{m}(t) := \mathbf{G}[\mathbf{x}(t), \mathbf{m}(t), \mathbf{u}(t), \mathbf{z}(t), \mathbf{y}(t), \mathbf{p}, t], \quad (2)$$

$$\mathbf{G} : \mathbb{R}^{n_x} \times \mathbb{R}^{n_m} \times \mathbb{R}^{n_u} \times \mathbb{R}^{n_z} \times \mathbb{R}^{n_y} \times \mathbb{R}^{n_p} \times \mathbb{R}^1 \mapsto \mathbb{R}^{n_m}.$$

Here \mathbf{x} denote continuous-time states, \mathbf{m} are discrete modes, \mathbf{u} and \mathbf{z} are controlled and not-controlled inputs, respectively, \mathbf{y} are outputs and \mathbf{p} are model parameters. Discrete modes are variables that change their values only at discrete time instants, so called event instants t_e . See [10] for more information on the treated hybrid DAE.

The Model aspect holds information related to the model, including

- Declaration of model variables in categories (Parameter, Input, Output, State, Generic),
- Values for model variables, e.g. for parameters,
- References to process signals, e.g. for inputs and outputs,
- Structural information for hierarchical sub-model structure,
- Reference to the implementation of the model.

The Model aspect does not provide any functionality nor does it deal with implementation details. Instead it references an external implementation. In this way available modeling tools can be applied and expensive re-implementation is avoided.

A model can be used to perform one or more model-based activities. A second aspect, the Dynamic Optimization aspect has been developed to interface a numerical solver, hold the solver configuration, and to exchange data between the solver and the control system. The exchanged data includes: configuration data, current process values (like sensor values and controller set-points), and history logs. Predictions are written back to the control system as history logs with future time stamps.

The integrated solver HQP is primarily intended for structured, large-scale nonlinear optimization [7]. It implements a Sequential Quadratic Programming algorithm that treats nonlinear optimization problems with a sequence of linear-quadratic sub-problems. The sub-problems are formed internally by simulating the model and by analyzing sensitivities. They are solved with an interior point method that is especially suited for a high number of inequality constraints, e.g. resulting from the discretization of path constraints. See [6], [8], and [7] for more details about the solver.

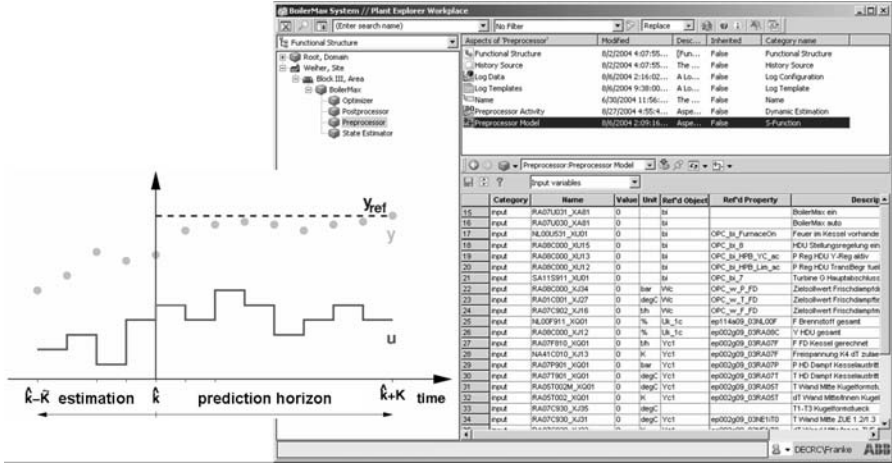


Fig. 1. Plant Explorer showing the Functional Structure of NMPC for boiler start-up (BoilerMax)

The treated model based activities include

- Initial value simulation for specified initial states $\mathbf{x}(t_0)$ and model inputs,
- Estimation of model parameters and initial states,
- Nonlinear optimal control with constraints on model inputs and outputs,
- Steady-state simulation, estimation and optimization at one time instant.

An initial-value simulation covers hybrid DAEs (1),(2). However, optimization and estimation problems can currently only be solved for a simplified hybrid DAE \mathbf{F} , \mathbf{G}' of the form:

$$\mathbf{m}(t) := \mathbf{G}'[\mathbf{m}(t), \mathbf{z}(t), t], \quad (3)$$

$$\mathbf{G}' : \mathbb{R}^{n_m} \times \mathbb{R}^{n_z} \times \mathbb{R}^1 \mapsto \mathbb{R}^{n_m},$$

where discrete modes do not depend on states or optimized variables.

Figure 1 shows how the functional structure is set up for an NMPC using Aspect Object technology. Different Aspect Objects represent the major processing activities of the NMPC algorithm.

- The Preprocessor reads current measurements from the underlying control system, validates the data and generates a guess for the model state. Furthermore a short term history is assembled.
- The State Estimator estimates the initial states based on the short-term history collected by the Preprocessor.
- The Optimizer predicts the optimal control into the future, starting from the estimated initial state

- The Postprocessor checks optimization results and communicates set points to the underlying control system.
- The Scheduler periodically triggers the other activities and supervises their successful completion.

The object-oriented, physical modeling technology Modelica is used to build the models [10]. A physical plant model is built on available model libraries [5]. It is used by both: state estimator and optimizer. Moreover, specific preprocessor and the postprocessor models are formulated as computational algorithms in Modelica. The scheduler model is formulated as state graph [12].

Based on the models, the activities are formulated as estimation (State Estimator), optimization (Optimizer) or initial-value simulation (Preprocessor, Postprocessor, Scheduler).

3 Application Example

A Nonlinear Model-based Predictive Controller (NMPC) for power plant start-up serves as example. The start-up problem is challenging as it is highly nonlinear in the covered large range of operation. Thermal stress occurring in thick walled components needs to be kept in given limits. Multiple manipulated variables must be coordinated. A long prediction horizon is required to fulfill the constraints during a start-up.

Figure 2 shows a process diagram of a power plant. Feed water goes through pre-heaters and the economizer into the evaporator, as seen in the lower left

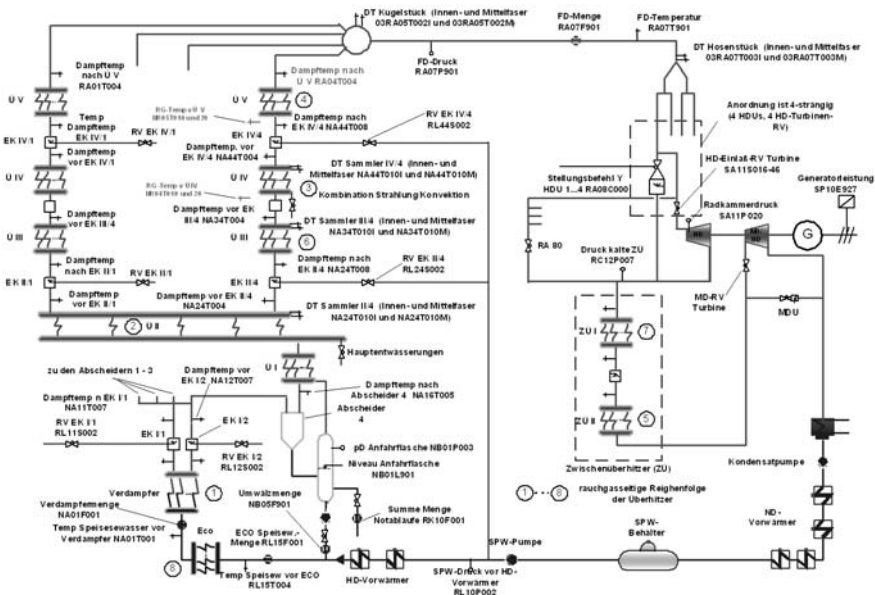


Fig. 2. Simplified process diagram of a power plant

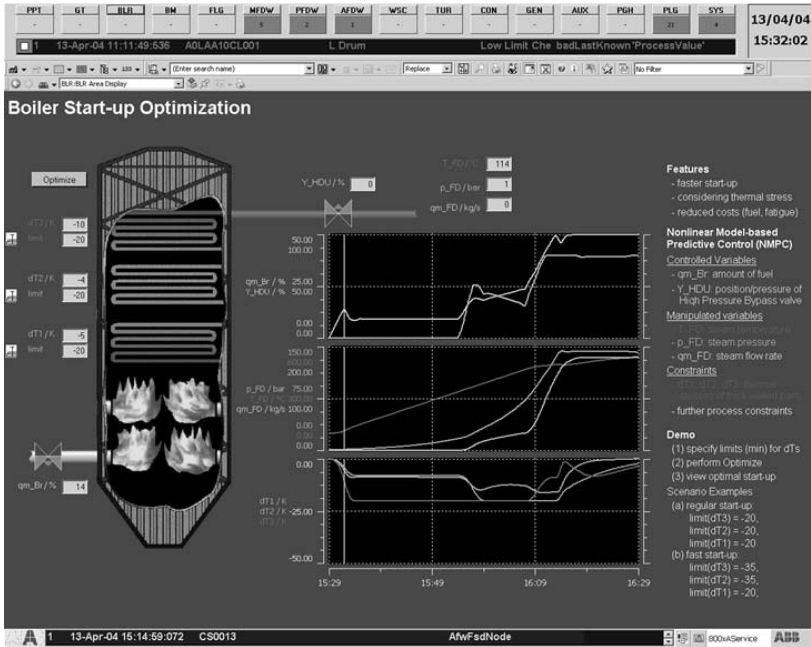


Fig. 3. Operator display showing the optimal start-up predicted by the NMPC, in addition to current process values and history logs

section of the diagram. Saturated steam leaving the evaporator is super-heated in several super-heater stages. The example uses five super-heater stages and four parallel streams, as seen in the upper left section of the diagram. The live steam leaving the boiler goes to the turbine. The example uses two turbine sections. In the turbine, thermal energy is transformed to mechanical energy, driving the generator. Afterwards the steam is condensed and water flows back to the feed water tank, as seen in the lower right section of the diagram.

A boiler model was built using the Modelica technology [5]. The model needs to be carefully designed so that it expresses the relationship between optimized control actions (fuel flow rate and valve positions) and constrained process values (pressures, temperatures and thermal stresses). In the example described here, a system of differential-algebraic equations (DAE) with 940 variables was built, using measurements of about 150 process values. The Dynamic Optimization aspect system was used off-line to identify model parameters based on data logs available for historical start-ups.

During a run of the NMPC, an optimization problem is solved on-line every minute. The model is adapted to the process based on 36 on-line signals. 18 values are communicated back to the process, including three controller set points and additional signals for switch conditions and operator displays. The time horizon for prediction and control is 90 minutes in the example. It gets divided into 90 sample periods. The optimized manipulated variables are parameterized

piecewise linear. All other model variables are evaluated at the sample time points. This means that overall 85540 variables are present in the on-line optimization problem. The solution time is about five minutes for a cold start of the solver and about 40 seconds for a subsequent solver run. Please see [8] for details about the numerical formulation and solution of the optimization problem.

Figure 3 shows an operator display for boiler start-up optimization. The trend plot displays the manipulated variables in the upper pane, the main process variables (live steam parameters) in the middle pane and constrained thermal stresses in the lower pane. As a result of the optimization, the process is driven along the allowed limits for thermal stresses.

Traditionally an operator display shows current process values and history logs. As a by-product of model predictive control, the operator can additionally see the prediction of the future behavior of the plant. As the NMPC runs integrated with the control system, this display can easily be configured.

Using the NMPC, the start-up time could be reduced by about 20 minutes and the start-up costs by 10% as compared to a well tuned classical control.

4 Conclusions

Nonlinear Model-based Predictive Control (NMPC) is a promising control technology. Due to advances in computational algorithms during recent years, it is now possible formulate and solve the underlying large-scale nonlinear optimization problems on-line under real-time conditions. The example discussed here was developed in detail in [8].

For a successful application of NMPC it is equally important to appropriately integrate the method with the control system. This paper discusses how this is done with the Industrial IT System 800xA by ABB. Based on international standards for control systems engineering and software, the System 800xA architecture and the Aspect Object technology allow a flexible integration of model knowledge and model based applications. Two new aspects have been developed in the Dynamic Optimization system extension. The new aspects can be combined with other available aspects, e.g. for controller connectivity, history logs and process graphics.

The NMPC runs on an application server that is integrated as additional node with the system. Installation and maintenance are identical to other nodes, like data servers and display clients.

This paper uses the start-up of a power plant as example. Batch processes are another promising application area, as described in [11].

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