Industrial Model Predictive Control
-- An Updated Overview

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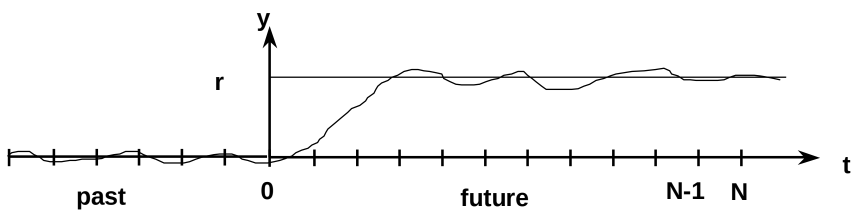


Outline

I. Introduction

II. A Brief History of MPC Technology

III. Survey of Industrial MPC Technology

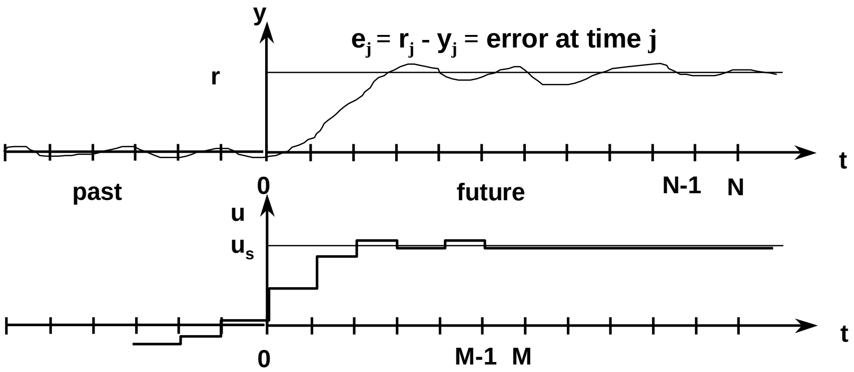
IV. Summary of Industrial MPC Applications

V. Future Directions

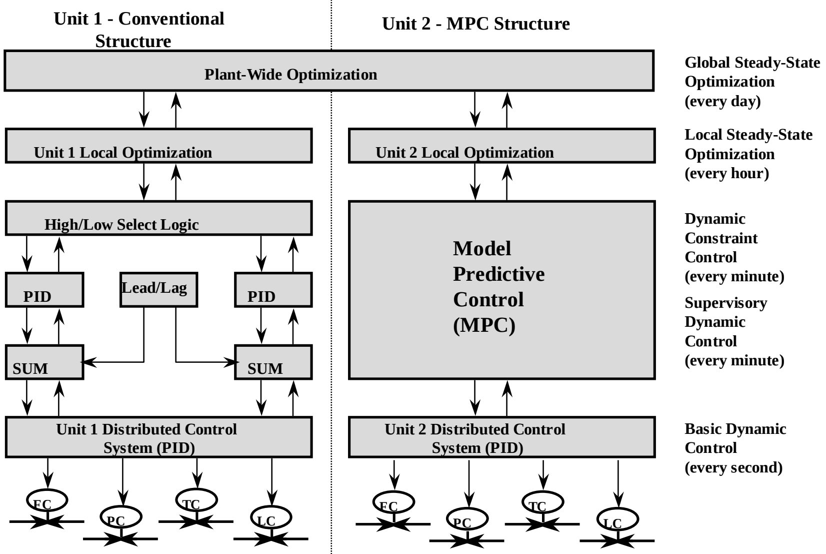
VI. Conclusions

MPC Definition

Model Predictive Control (MPC) **refers to a class of algorithms that utilize an explicit *process model* to compute a manipulated variable profile that will optimize an open-loop performance objective over a future time interval. The performance objective typically penalizes *predicted future errors* and manipulated variable movement subject to constraints.**



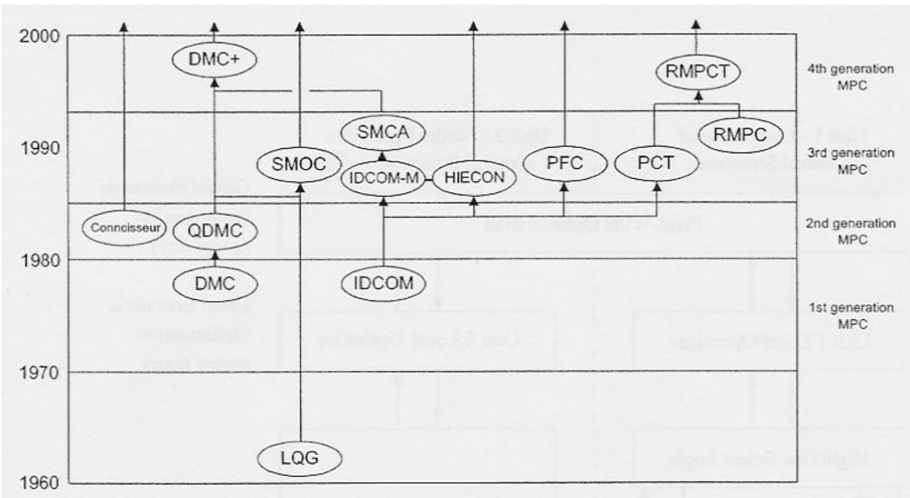
Multivariable Process Control System



A Brief History of MPC

Algorithm	Model	Objective	Pred. Horiz	Constraints	Feedback
LQG (1960)	L SS	min ISE IO	infinity	-	KF
IDCOM (1976)	L conv	min ISE O	p	IO	output bias
DMC (1979)	L conv	min ISE IOM	p	IO	output bias
QDMC (1983)	L conv	min ISE IOM	p	IO	output bias
GPC (1987)	L ARMA	min ISE IO	p	-	output bias
IDCOM-M (1988)	L conv	min ISE O min ISE I	p	IO	output bias
SMOC (1988)	L SS	min ISE IO	p	IO	KF
Rawlings and Scokaert (1996)	L SS	min ISE IOM	infinity	IO	KF
Process Perfecter (1997)	N NN	min ISE IO	p	IO	output bias
NOVA-NLC (1997)	N FP	min ISE IO	p	IO	output bias
Allgower et al. (1998)	N SS	min ISE IO	infinity	IO	MHE

Genealogy of linear MPC algorithms

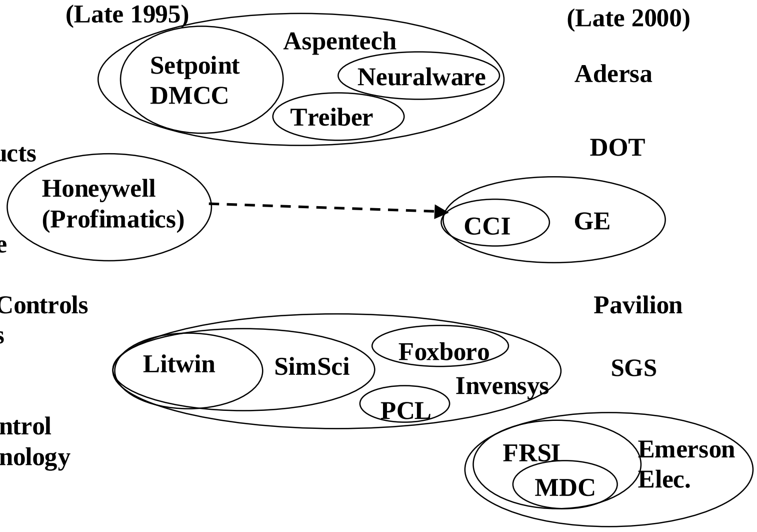


MPC Industry Consolidation

CPC-V **Update**

(Late 1995) **(Late 2000)**

Adersa
CCI
DMCC
DOT Products
Honeywell
Litwin
Neuralware
Pavilion
Predictive Controls
Profimatics
Shell
Setpoint
Treiber Control
MDC Technology



Survey of MPC Technology Products

- **We surveyed eight major MPC vendors to determine the current state of industrial MPC technology**
  - **Five linear MPC products**
  - **Five nonlinear MPC products**
  - **Information provided by vendors beginning in mid-1999**
- **Most established vendors were asked to participate. The list of vendors is representative, not exhaustive**
- **Vendors were asked to fill out a written survey, reporting only non-proprietary information**
- **Our goal is to determine the state of the art; not to judge the relative merits of one vendor’s technology versus another**

Linear MPC Vendors and Products

- **We surveyed five MPC vendors to determine the current state of industrial linear MPC applications:**

– **Adersa**	**PFC** ***(Predictive Functional Control)***
	HIECON ***(Hierarchical Constraint Control)***
	GLIDE ***(Identification)***
– **Aspentech**	**DMCplus** ***(Dynamic Matrix Control plus)***
	DMCplus-Model ***(Identification)***
– **Honeywell**	**RMPCT** ***(Robust MPC Technology)***
– **PCL**	**Connoisseur** ***(Control and ID)***
– **Shell Global Solutions**	**SMOC** ***(Shell Multivariable Optimizing Control)***
	AIDA ***(Identification)***

- **Yokogawa and MDC have licensed versions of SMOC**

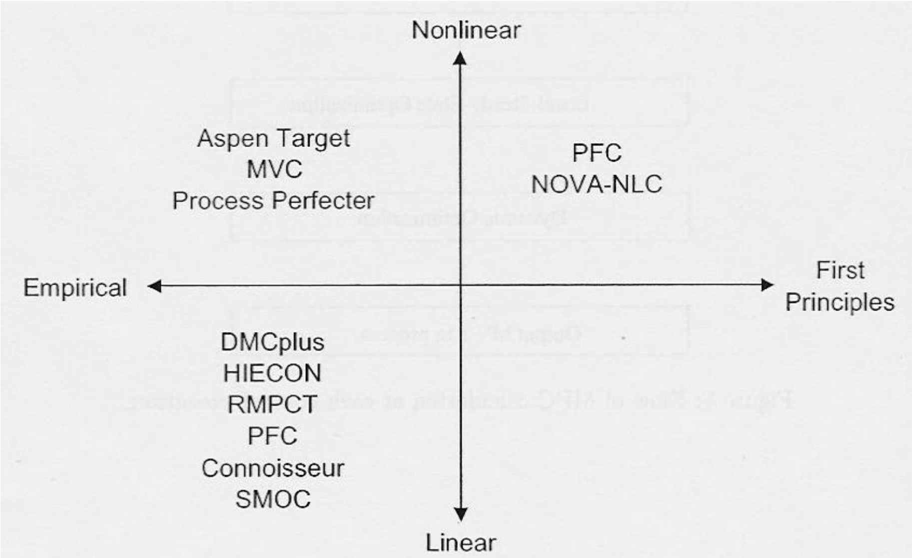
Nonlinear MPC Vendors and Products

- **We surveyed five NMPC vendors to determine the current state of industrial NMPC technology:**

– **Adersa**	**PFC (Predictive Functional Control)**
– **Aspen Technology**	**Aspen Target**
– **Continental Controls**	**MVC (Multivariable Control)**
– **DOT Products**	**NLC (NOVA Nonlinear Controller)**
– **Pavilion Technologies**	**Process Perfecter**

- **A product must use a nonlinear dynamic model to be included in the survey**

Process Model Types



Linear Models: Identified from process data

- **Most products use PRBS-like or multiple steps test signals. Glide uses non-PRBS signals**
- **Most products use FIR, ARX or Step response models**
  - **Glide uses Transfer function G(s)**
  - **RMPCT uses Box-Jenkins**
  - **SMOC uses state space models**
- **Most products use least squares type:**
  - **equation error or output error methods**
  - **RMPCT uses prediction error method**
  - **Glide uses a global method to estimate uncertainty**
- **Connoisseur has adaptive capability using RLS**
- **A few products (DMCplus, SMOC) have subspace identification methods available**
- **Most products have uncertainty estimate, but most products do not make use of the uncertainty bound in control design**

Nonlinear Models: Process data or first principles

- **Nonlinear Identification**
  - **Most products use nonlinear identification for nonlinear model development**
  - **Process Perfecter uses pulse tests for dynamics and historical data for static nonlinearity**
  - **Aspen Target identifies a core linear state-space model with an additive nonlinear neural net**
  - **Most products provide confidence limits or safeguards against extrapolation**
  - **Linear models are used as back-up**
- **First Principles Modeling**
  - **NOVA-NLC uses first principles models (mass and energy balances)**

Nonlinear State-Space Models

- **Aspen Target uses a state space model form:**

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}_u\mathbf{u}_k + \mathbf{B}_v\mathbf{v}_k$$
$$\mathbf{y}_k = \mathbf{g}(\mathbf{x}_k) = \mathbf{C}\mathbf{x}_k + \mathbf{NN}(\mathbf{x}_k)$$

  - **Linear dynamics is built by a series of first order filters or Laguerre models**
  - **The output C matrix is built using PLS and NN is a neural network nonlinear mapping**
  - **Model reduction is performed between the state and output equations**
  - **A model confidence index is derived from identification. The NN portion is turned off during extrapolation**

Nonlinear Input-Output Models

- **MVC and Process Perfecter use input-ouput model with static nonlinearity and linear dynamics.**
- **A linear ARX model is built around a steady state using deviation variables (using plant test data)**
- **A static nonlinear model is built over a wide operating region (using historical data)**
- **At each control calculation,**
  - **the static nonlinear model is linearized around the initial and final steady state to obtain the gains; then a linear interpolation is used between the two gains as a function of inputs**
  - **the linear dynamic model is re-scaled to match this gain**
- **Effectively a quadratic model is used at each step**

A General MPC Calculation

Read MV, CV, DV, and other process measurements

↓

Output feedback (state estimation)

↓

Determine controlled process subset

↓

Remove ill-conditioning

↓

Steady state target optimization

↓

Dynamic optimization

↓

Output MV's to process

Control: Output Feedback

• For stable processes, all of the algorithms surveyed here use the same form of feedback, based on comparing the current measured output to the predicted output:

$$\mathbf{b}_k = \mathbf{y}_k^m - \mathbf{y}_k$$

The bias term is then added to the model for subsequent predictions:

$$\mathbf{y}_{k+j} = \mathbf{g}(x_{k+j}) + \mathbf{b}_k$$

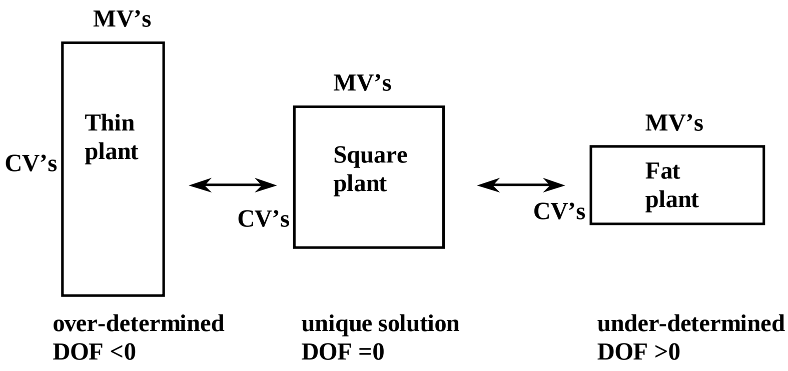
• This form of feedback is only optimal for an output disturbance that remains constant for all future time; it does, however, remove steady state offset (Rawlings, et al. 1994).

• Variations of this approach are used for integrating dynamics, usually by combining bias terms from the output and the rate of change of the output in some way.

• Output feedback via Kalman filters is an option for a few vendors (SMOC, Aspen Target, DOT)

Control: Controlled Sub-Process

• At each control execution the controller must determine which MV's can be manipulated and which CV's should be controlled
• These decisions are made based on operator input, measurement status, and status of the underlying MV control loops
• The *shape* of the controlled sub-process can therefore change at each control execution:



Control: Removal of Ill-Conditioning

• **As the controlled sub-process changes in real-time, the controller must detect and remove ill-conditioning before it results in erratic MV movement**

• **Because ill-conditioning is a *process* problem it can be addressed only by modifying the internal model or by giving up on control specifications**

• **Three strategies are currently used to address ill-conditioning: Singular Value Thresholding, Controlled Variable Ranking, and Move Suppression**

- **Singular Value Thresholding involves decomposing the process using SVD; singular values below a given threshold are discarded**

- **Controlled Variable Ranking involves discarding low priority CVs until the condition number is reasonable**

- **Input Move Suppression can also be used; input move suppression will improve the condition number similar to ridge regression**

Control: Local Steady-State Optimization

• **Most controllers use a separate steady-state optimization to determine steady-state targets for the inputs and outputs**

• **Most controllers provide a Linear Program (LP) option for SS optimization; the LP is used to enforce input and output constraints and determine optimal input and output targets for the thin and fat plant cases**

• **Most controllers also provide a Quadratic Program (QP) option to compute the steady-state targets**

• **All controllers enforce hard MV constraints at steady-state; CV constraint formulations vary**

• **The DMCplus controller solves a sequence of separate QPs to determine optimal input and output targets; CV's are ranked in priority so that SS control performance of a given CV will never be sacrificed to improve performance of lower priority CV's; MV's are also ranked in priority order to determine how extra degrees of freedom is used.**

Control: Dynamic Optimization

A vector of inputs $\mathbf{u}^M$ is found which minimizes J subject to constraints on the inputs and outputs:

$$J = \sum_{j=1}^{P} \left\| \mathbf{e}_{k+j}^{y} \right\|_{\mathbf{Q}_j}^{q} + \sum_{j=0}^{M-1} \left\| \Delta \mathbf{u}_{k+j} \right\|_{\mathbf{S}_j}^{q} + \sum_{j=0}^{M-1} \left\| \mathbf{e}_{k+j}^{u} \right\|_{\mathbf{R}_j}^{q} + \left\| \mathbf{s} \right\|_{\mathbf{T}}^{q}$$

$$\mathbf{u}^{\mathbf{M}} = \left(\mathbf{u}_0^T, \mathbf{u}_1^T, \ldots \mathbf{u}_{M-1}^T \right)^T$$

$$\mathbf{x}_{k+1} = \mathbf{f}\left(\mathbf{x}_k, \mathbf{u}_k \right)$$

$$\mathbf{y}_{k+1} = \mathbf{g}\left(\mathbf{x}_{k+1} \right) + \mathbf{b}_k$$

$$\underline{\mathbf{y}} - \mathbf{s} \le \mathbf{y}_k \le \overline{\mathbf{y}} + \mathbf{s}$$

$$\underline{\mathbf{u}} \le \mathbf{u}_k \le \overline{\mathbf{u}}$$

$$\Delta \underline{\mathbf{u}} \le \Delta \mathbf{u}_k \le \Delta \overline{\mathbf{u}}$$

$$\mathbf{s} \ge \mathbf{0}$$

Control: Dynamic Optimization

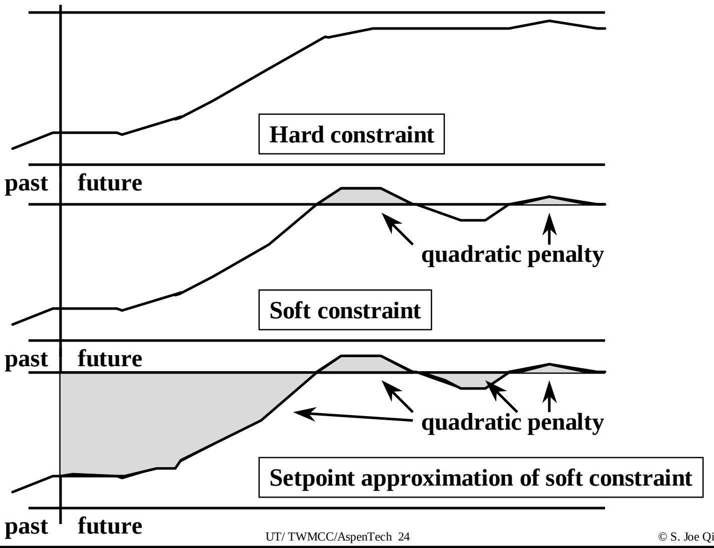
- **Most control algorithms use a single quadratic objective**
- **The HIECON algorithm uses a sequence of separate dynamic optimizations to resolve conflicting control objectives; CV errors are minimized first, followed by MV errors**
- **Connoisseur allows for a multi-model and adaptive approaches**
- **The Process Perfecter uses variable trajectory weights Q_j to increase the output error penalty over the prediction horizon**
- **The RMPCT algorithm defines a funnel and finds the optimal trajectory $\mathbf{y}^r$ and input $\mathbf{u}^M$ which minimize the following objective:**

$$\min_{\mathbf{y}_{k+j}^r, \mathbf{u}^M} J = \sum_{j=1}^{P} \left\| \mathbf{y}_{k+j}^r - \mathbf{y}_{k+j} \right\|_{\mathbf{Q}}^2 + \left\| \mathbf{u}_{M-1} - \mathbf{u}_{ss} \right\|_{\mathbf{S}}^2$$

subject to a funnel constraint: $\underline{\mathbf{y}}_j \le \mathbf{y}_{k+j}^r \le \overline{\mathbf{y}}_j$

Control: Constraint Formulations

• There are two basic types of constraints: hard and soft Hard constraints are never violated; soft constraints may be violated but the violation is minimized
• Soft constraints are sometimes approximated using a setpoint



Control: Constraint Formulations

• All of the algorithms allow hard MV maximum, minimum and rate of change constraints; the PFC algorithm also enforces hard MV acceleration constraints

• Most algorithms enforce soft CV constraints

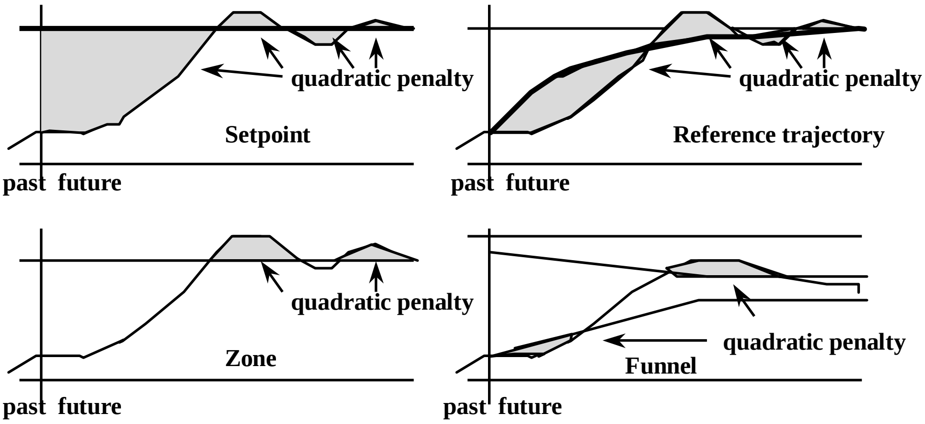
• Enforcing hard CV constraints may lead to an infeasible program or to a feasible solution that is closed loop unstable; for this reason the hard CV constraint formulations differ considerably

• The DMCplus and RMPCT algorithms consider hard output constraints only in the steady-state optimization

• The HIECON, PFC, and NOVA-NLC algorithms consider hard output constraints in the dynamic optimization; in HIECON and PFC these are ranked so that low priority constraints can be dropped to recover feasibility

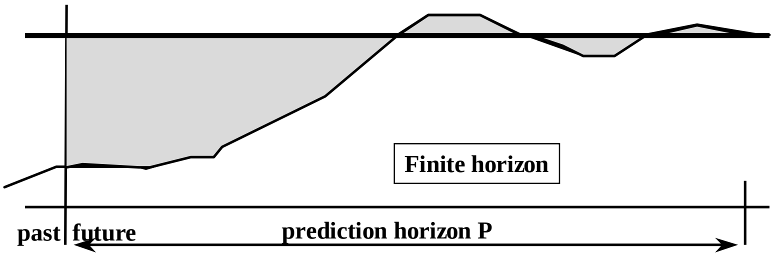
Control: Output Trajectories

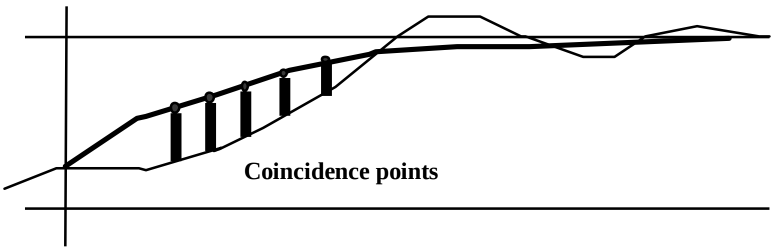
- **There are four ways to specify future output behavior: setpoint, zone, reference trajectory and funnel**
- **Move suppression is necessary when reference trajectory is not used**



Control: Output Horizon

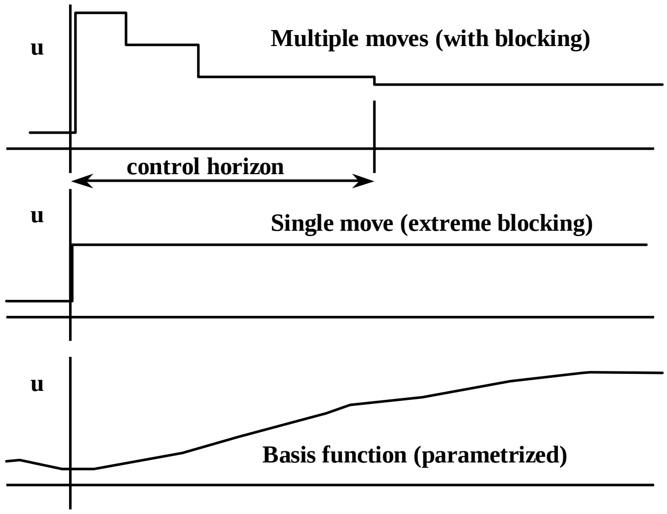
There are two ways to parameterize the output horizon; finite horizon and coincidence points





Control: Input Parameterization

There are three options for parameterizing the input signal; multiple move, single move, and basis functions



Linear MPC Control Technology

Company	**Aspen Tech**	**Honeywell Hi-spec**	**Adersa**	**Adersa**	**PCL**	**SGS**
Product	**DMCplus**	**RMPCT**	**HIECON**	**PFC**	**Connois.**	**SMOC**
Model forms	FSR L,S,I,U	ARX,TF L,S,I,U	FIR L,S,I	LSS,TF,ARX L,S,I,U	ARX,FIR L,S,I,U	LSS L,S,I,U
Feedback	CD,ID	CD,ID	CD,ID	CD,ID	CD	KF
SS Opt.	L/Q[I,O],...,R	L/Q[I,O]	-	Q[I,O]	L[I,O]	Q[I,O],R
Dyn. Opt.	Q[I,O,M],S	Q[I,O]	Q[O],Q[I]	Q[I,O],S	Q[I,O,M]	Q[I,O]
Output Traj.	S,Z	S,Z,F	S,Z,RT	S,Z,RT	S,Z	S,Z,RT
Output Horiz.	FH	FH	FH	CP	FH	FH
Input Param.	MMB	MM	SM	BF	MMB	MMB
Other features					Adaptive	

Nonlinear MPC Control Technology

Company	Adersa	Aspen Tech	Continental Controls	DOT Products	Pavilion
Product	**PFC**	**Aspen Target**	**MVC**	**NOVA NLC**	**Process Perfecter**
Model forms	NSS-FP S,I,U	NNN-NSP S,I,U	SNP-ARX S,I,U	NSS-FP S,I,U	NNN-ARX S,I,U
Feedback	CD,ID	CD,ID,EKF	CD,ID	CD,ID	CD
SS Opt.	Q[I,O]	Q[I,O]	Q[I,O]	Q[I,O]	Q[I,O]
Dyn. Opt.	Q[I,O],S	Q[I,O],S	Q[I,O,M]	(Q,A)[I,O,M]	Q[I,O]
Output Traj.	S,Z,RT	S,Z,FT	S,Z,RT	S,Z,RTUL	S,Z,TW
Output Horiz.	CP	CP	FH	FH	FH
Input Param.	BF	MM	SM	MM	MM

Control: Design and Tuning

- **The MPC control design and tuning procedure is described as follows:**

  1. From the stated control objectives, define the size of the problem, and determine the relevant CV's, MV's and DV's
  2. Test the plant systematically by varying MV's and DV's; capture and store the real-time data showing how the CV's respond
  3. Derive a dynamic model from the plant test data using an identification package, or estimate parameters for a first-principles model
  4. Configure the MPC controller and enter initial tuning parameters
  5. Test the controller off-line using closed loop simulation to verify the controller performance
  6. Download the configured controller to the destination machine and test the model predictions in *open-loop* model
  7. Commission the controller and refine the tuning as needed

- **Tuning knobs are available to trade-off between performance and robustness**

MPC Applications Summary

- **Total number of reported applications is 4600*, up from 2200 in late 1995**
- **Majority of applications (67%) are in refining and petrochemicals**
- **Chemical and pulp & paper come in 2^{nd} and 3^{rd}**
- **Applications reported in a wide range of other areas, including food, automotive, and aerospace industries**
- **Caution: different vendors may count applications differently**

*** This number does not include in-house implementations by operating companies**

Linear MPC Applications

Area	Aspen Tech	Honeywell Hi-Spec	Adersa	PCL	SGS	Total
Refining	1200	480	280	25		1985
Petrochemicals	450	80		20		550
Chemicals	100	20	3	21		144
Pulp and Paper	18	50				68
Air and Gas		10				10
Utility		10		4		14
Mining/Metallurgy	8	6	7	16		37
Food Processing			41	10		51
Polymer	17					17
Furnaces			42	3		45
Aerospace/Defense			13			13
Automotive				7		7
Unclassified	40	40	1045	26	450	1601
Total	1833	696	1438	125	450	4542

Nonlinear MPC Applications

Area	Adersa	Aspen Tech	Continental Controls	DOT Prodcuts	Pavilion	Total
Air and Gas			18			18
Chemicals	2		15		5	22
Food Processing					9	9
Polymer		1		5	15	21
Pulp and Paper					1	1
Refining					13	13
Utilities		5	2			7
Unclassified	1		1			2
Total	3	6	36	5	43	93

Next-Generation MPC Technology

- **Models:** nonlinear models from first principles, linear state-space models, adaptive capabilities
- **Output feedback:** state estimation using unmeasured disturbance models, Kalman filters, moving horizon estimation
- **Dynamic optimization:** multiple objective functions, infinite prediction horizon, incorporation of model uncertainty, input parameterization by basis functions
- **Numerical solution:** highly structured methods that exploit recent developments (interior point methods)
- **User interface:** simplified interfaces that hide complexity, sensible default tuning
- **Platforms:** tight integration into DCS, tight integration into supply-chain systems
- **Markets:** further extension into non-traditional markets such as microelectronics, automotive, pulp&paper

Future Needs for MPC Technology

- **Model Development:** Need tools that allow seamless integration of first principles with process data
- **Output feedback:** need to further develop state estimation and disturbance modeling technologies
- **Dynamic optimization:** Need nominally stabilizing infinite-horizon formulations
- **Numerical solution:** Need to exploit recent developments (interior point methods)
- **Robustness:** Need to incorporate model uncertainty from identification into the control calculation
- **Justification of NMPC:** Need systematic methods to determine when MPC can be justified, and when nonlinear MPC is required.

Conclusions

- **MPC technology has been applied to a wide variety of control problems with over 4600 reported applications, up from 2200 in 1995**
- **Major recent trends are consolidation of vendors and development of nonlinear MPC technology**
- **Nonlinear MPC technology has been applied to small problems in areas where the linear technology has fared poorly, such as in polymer processing**
- **Each MPC product has specific plusses and minuses; the most important consideration in choosing a vendor is their experience with the specific process and control problem under consideration**
- **The most significant challenges today for MPC technology are:**
  - **nonlinear model development**
  - **state estimation and disturbance modeling**
  - **rapid and reliable real-time optimization**
  - **justification criteria**

Acknowledgments

• **The authors thank the MPC vendors for their time and effort in completing the survey and answering our follow-up questions**