4.1 Model Predictive Control

Prof. Davide Fissore
Politecnico di Torino, Italy
davide.fissore@polito.it

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Digitalization Tools for the Chemical and Process Industries

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Outline

1. Historical overview
2. Digital control and Model Predictive control
3. The Model
4. Disturbance estimation
5. Steady-state and dynamic optimization
6. Pros & cons
7. Example

Historical overview

Том XXIV «АВТОМАТИКА И ТЕЛЕМЕХАНИКА» № 7

1963

УДК 62-50

ПРИМЕНЕНИЕ МЕТОДОВ ЛИНЕЙНОГО ПРОГРАММИРОВАНИЯ ДЛЯ СИНТЕЗА ИМПУЛЬСНЫХ АВТОМАТИЧЕСКИХ СИСТЕМ

А. И. ПРОПОЙ

(*Москва*)

A. I. Propoi, Application of linear programming methods for the synthesis of automatic sampled-data systems, *Avtomat. i Telemekh.*, 1963, Volume 24, Issue 7, 912–920

Historical overview

DMC Shell

Automatica
Volume 14, Issue 5, September 1978, Pages 413-428

ELSEVIER

Paper

Model predictive heuristic control: Applications to industrial processes ☆

J. Richalet †, A. Rault †, J.L. Testud †, J. Papon †

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https://doi.org/10.1016/0005-1098(78)90001-8

IDCOM Adersa-Gerbios

DYNAMIC MATRIX CONTROL™ — A COMPUTER CONTROL ALGORITHM

PRESENTED AT:

THE NATIONAL MEETING OF
THE AMERICAN INSTITUTE OF CHEMICAL ENGINEERS
HOUSTON, TEXAS
APRIL 1979

BY:

DR. CHARLES R. CUTLER
(DYNAMIC MATRIX CONTROL CORPORATION)
&
DR. B.L. RAMAKER
(SHELL OIL COMPANY)

GRUPPO DI INGEGNERIA CHIMICA DELL'UNIVERSITA'
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Historical overview

CA CITTADINA

VENERDI' 30 NOVEMBRE 1973
ANNO 107 - NUMERO 282

Dalle 12 di domani alle 24 di domenica chiusi i benzinai

Austerity, conto alla rovescia

La prefettura assediata da richieste - Possono circolare di festa, tra gli altri (ma solo per soccorsi urgenti), medici, ostetriche, veterinari, autoveicoli per trasporto dei giornali - Oggi il rilascio dei lasciapassare provvisori: serviranno solo per il 2 dicembre - I problemi dei comuni di provincia in un incontro col prefetto - Protesta degli autonoleggiatori

Iniziative ecologiche: dopodomani tutti in piazza Vittorio con la "bici"

Historical overview

Energy crisis + global competition + environmental reg.

- Process integration
- Reduced design, safety margins
- Real time optimization
- Tighter quality control

Higher demand on process control

Historical overview

Company	Acronym	Product Name (Function)
Adersa	HIECON PFC GLIDE	Hierarchical Constraint Control Predictive Functional Control (Identification package)
DMC Corp.	DMC DMI	Dynamic Matrix Control Dynamic Matrix Identification
Honeywell Profimatics	RMPCT PCT	Robust Model Predictive Control Technology Predictive Control Technology
Setpoint Inc.	SMCA SMC-Idcom SMC-Test SMC-Model	Setpoint Multivariable Control Architecture (Multivariable control package) (Plant test package) (Identification package)
Treiber Controls	OPC	Optimum Predictive Control

Qin, Joe & Badgwell, Thomas. (1997). An Overview Of Industrial Model Predictive Control Technology. AIChE Symposium Series. 93.

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Historical overview

Area	DMC Corp.	Setpoint Inc.	Honeywell Profimatics	Adersa	Treiber Controls	Total
Refining	360	320	290	280	250	1500
Petrochemicals	210	40	40	-	-	290
Chemicals	10	20	10	3	150	193
Pulp and Paper	10	-	30	-	5	45
Gas	-	-	5	-	-	5
Utility	-	-	2	-	-	2
Air Separation	-	-	-	-	5	5
Mining/Metallurgy	-	2	-	7	6	15
Food Processing	-	-	-	41	-	41
Furnaces	-	-	-	42	-	42
Aerospace/Defense	-	-	-	13	-	13
Automotive	-	-	-	7	-	7
Other	10	20	-	45	-	75
Total	600	402	377	438	416	2233
First App	DMC:1985	IDCOM-M:1987 SMCA:1993	PCT:1984 RMPCT:1991	IDCOM:1973 HIECON:1986	OPC:1987	

Qin, Joe & Badgwell, Thomas. (1997). An Overview Of Industrial Model Predictive Control Technology. AIChE Symposium Series. 93.

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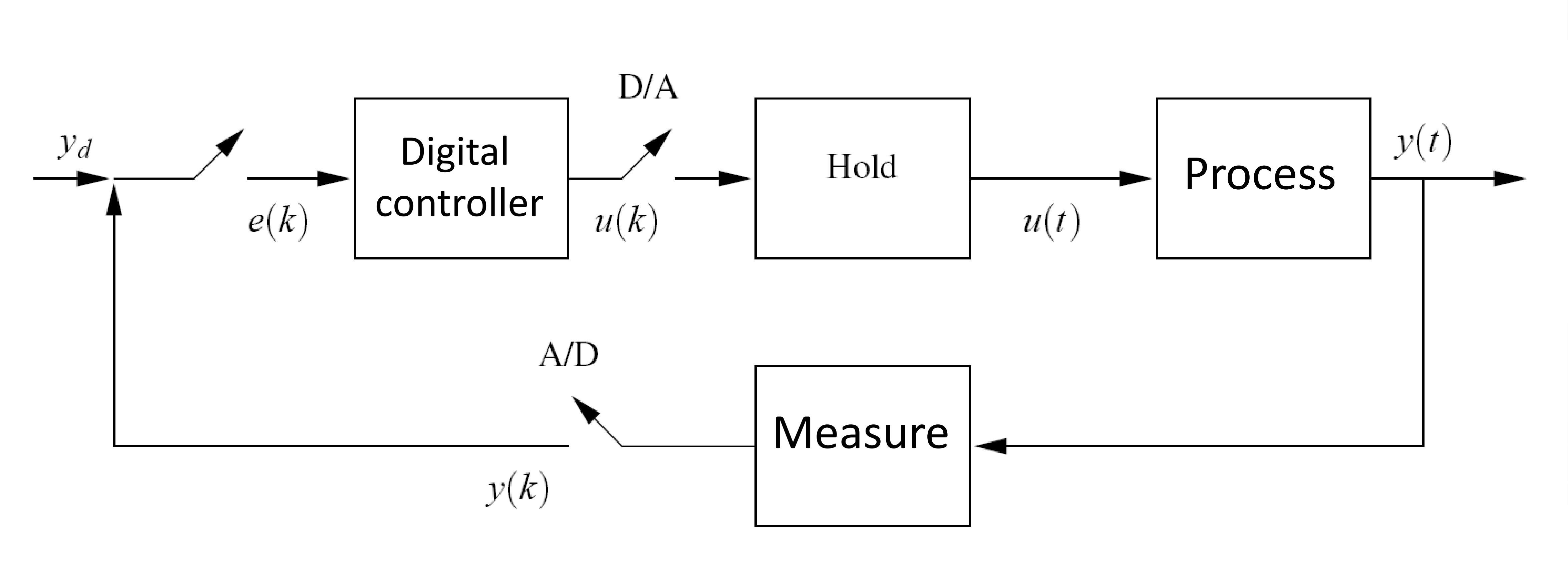
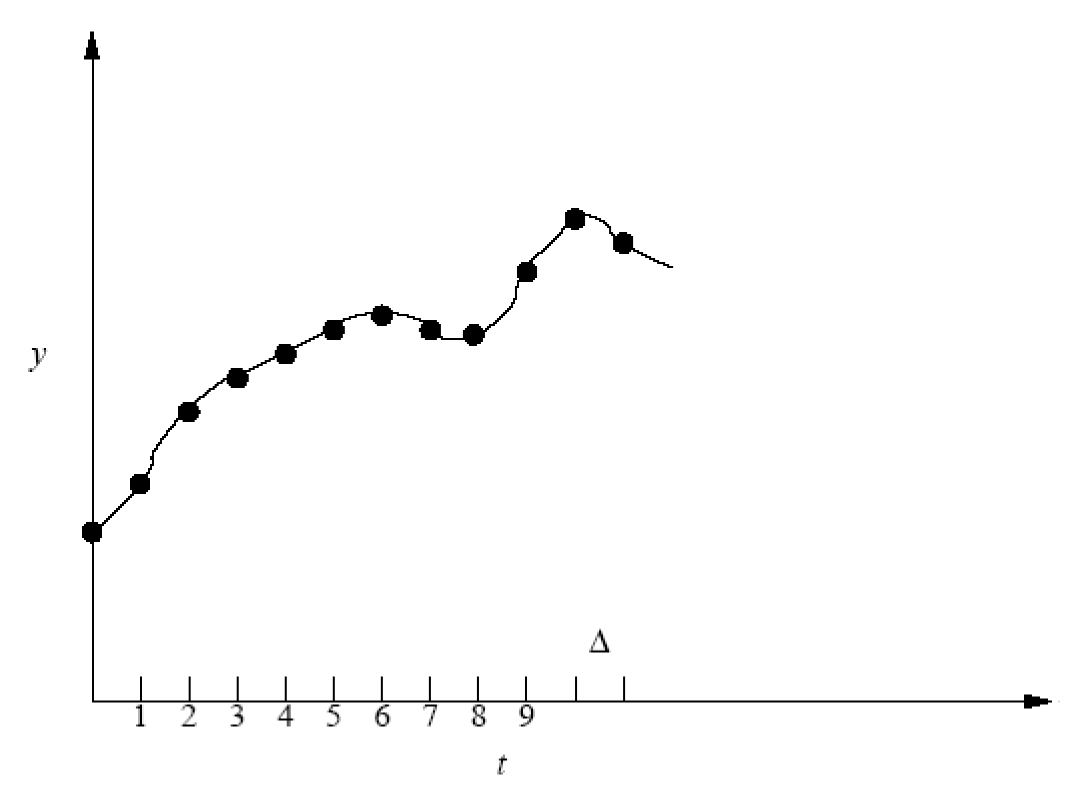
Digital control

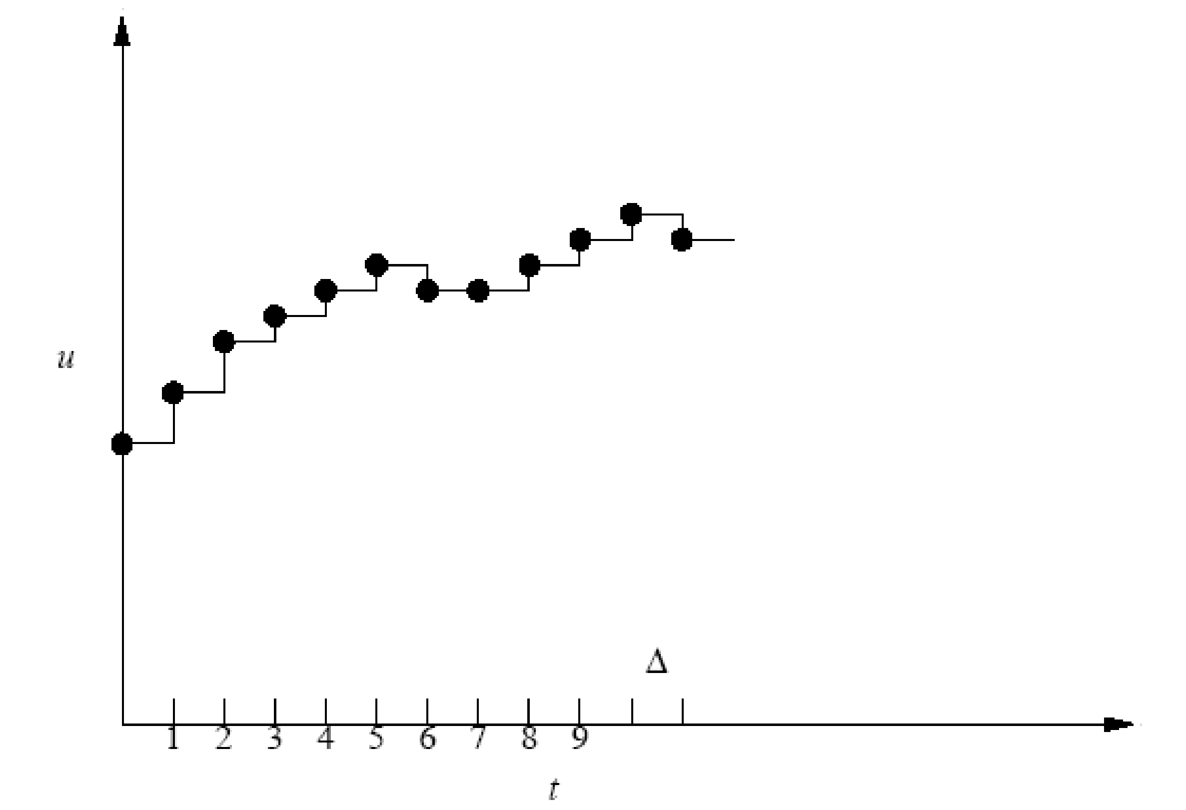


Digital control

Sampler



Holder



Model Predictive Control

Model Predictive Control

The best material model of a cat is another, or preferably the same, cat.

THE ROLE OF MODELS IN SCIENCE

ARTURO ROSENBLUETH AND NORBERT WIENER

The intention and the result of a scientific inquiry is to obtain an understanding and a control of some part of the universe. This statement implies a dualistic attitude on the part of scientists. Indeed, science does and should proceed from this dualistic basis. But even though the scientist behaves dualistically, his dualism is operational and does not necessarily imply strict dualistic metaphysics.

Model Predictive Control

A theory has only the alternative of being right or wrong. A model has a third possibility: it may be right, but irrelevant (Egan)

Model Predictive Control

Linear time-invariant discrete-time model

$$\begin{cases} x(k+1) = \tilde{A}x(k) + \tilde{B}u(k) \\ y(k) = \tilde{C}x(k) + \tilde{D}u(k) \\ x(0) = x_0 \end{cases}$$

$t = k\Delta$, $k = 0, 1, 2, \ldots$

$$\begin{cases} x_{k+1} = \tilde{A}x_k + \tilde{B}u_k \\ y_k = \tilde{C}x_k + \tilde{D}u_k \end{cases}$$

x_0 known

$$x_1 = \tilde{A}x_0 + \tilde{B}u_0$$

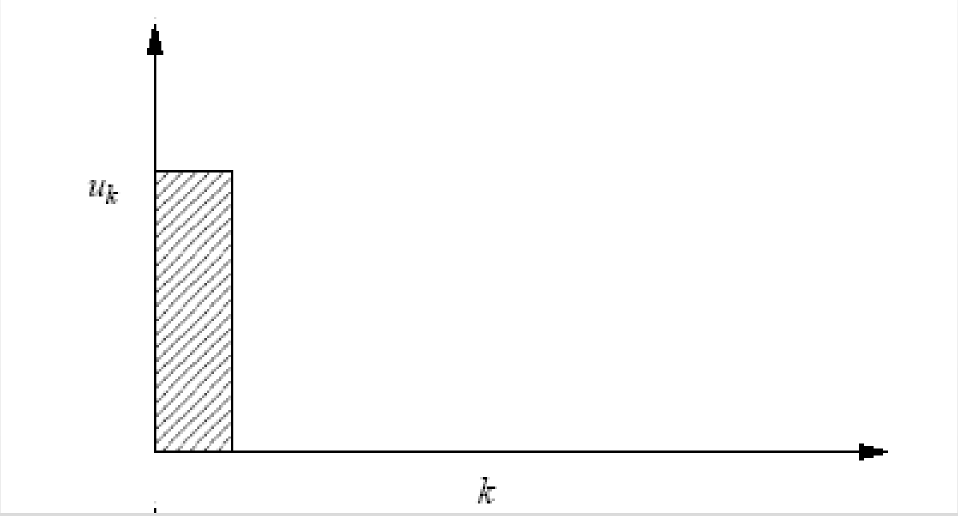
$$x_2 = \tilde{A}x_1 + \tilde{B}u_1 = \tilde{A}\left(\tilde{A}x_0 + \tilde{B}u_0\right) + \tilde{B}u_1 = \tilde{A}^2x_0 + \tilde{A}\tilde{B}u_0 + \tilde{B}u_1$$

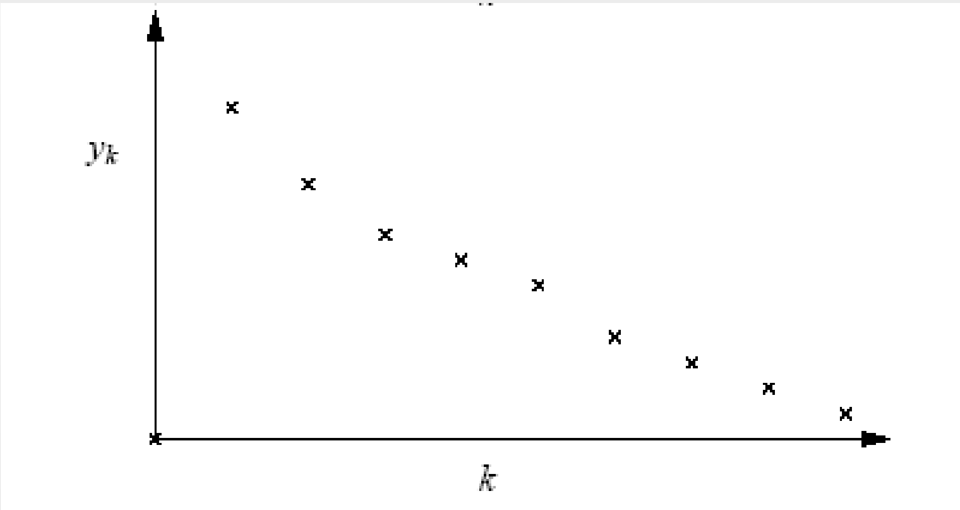
...

$$x_k = \tilde{A}^k x_0 + \sum_{j=0}^{k-1} \tilde{A}^{k-j-1}\tilde{B}u_j$$

Model Predictive Control

Convolution model: FIR (*Finite Impulse Response*)





$$y_k = \sum_{j=0}^{\infty} h_j u_{k-j}$$

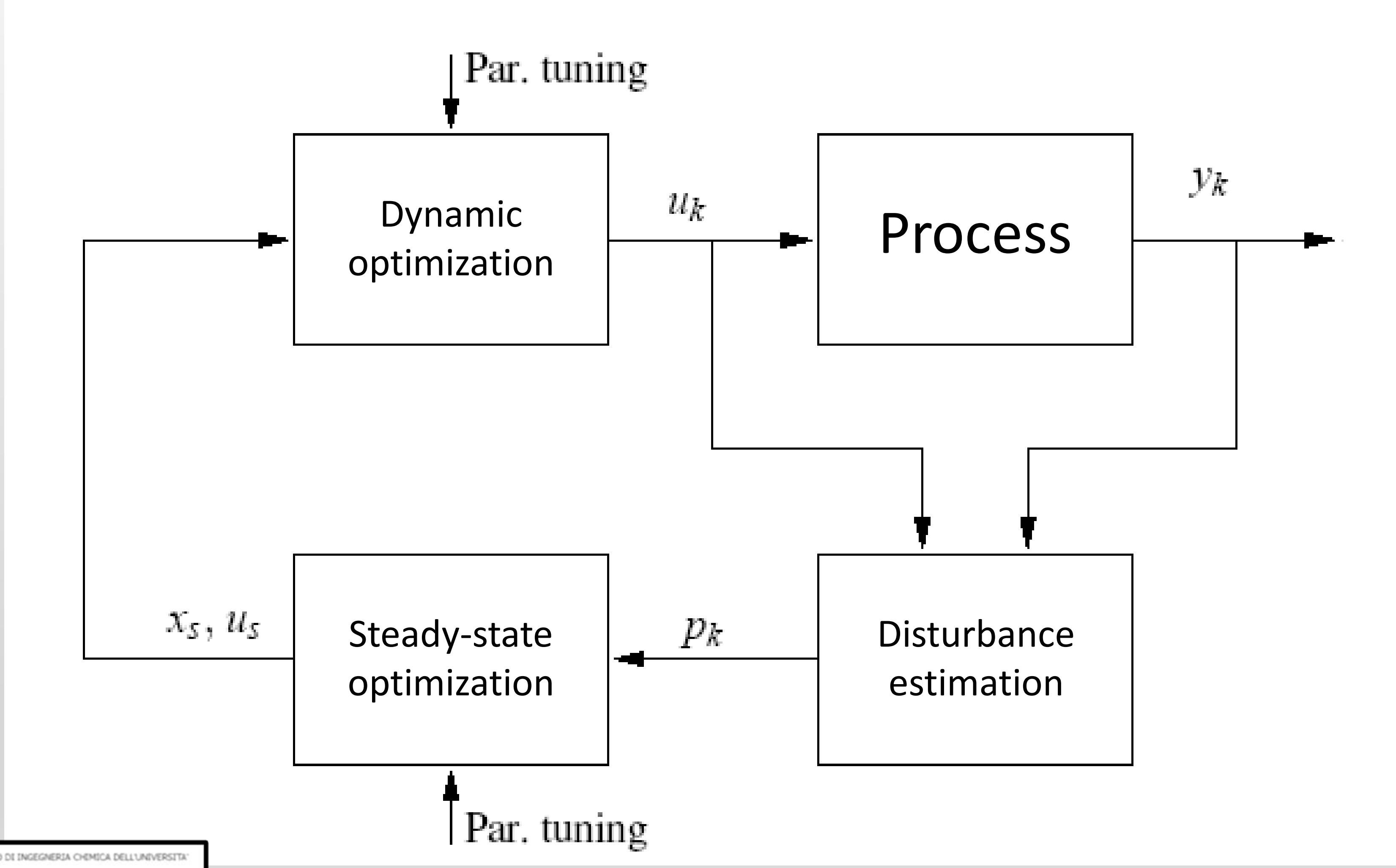
Model Predictive Control

Convolution model: SRM (*Step Response Method*)

$$y_k = \sum_{j=1}^{\infty} s_j \Delta u_{k-1}$$

$$\Delta u_{k-1} = u_k - u_{k-1},\ s_j = \sum_{i=0}^{j} h_j$$

Model Predictive Control



$$x_{k+1} = Ax_k + Bu_k$$
$$\hat{y}_k = Cx_k + p_k$$

$$p_k = y_k - Cx_k$$

Steady-state optimization

The goal is to find optimal stationary values for **states** and **inputs**.

Let us initially consider the case in which the system to be controlled has the same number of controlled and manipulated variables and there are no constraints on the manipulated variables.

Once the desired value (set-point) of the controlled variables has been fixed, the stationary value of the inputs and states can be calculated by solving the following square linear system:

$$\begin{bmatrix} I-A & -B \\ C & 0 \end{bmatrix} \begin{bmatrix} x_s \\ u_s \end{bmatrix} = \begin{bmatrix} 0 \\ y^{sp} - p_k \end{bmatrix}$$

where x_s and u_s represent the stationary values of the states and inputs calculated at instant k, using the disturbance term p_k. These values must therefore be recalculated at each sampling instant.

Steady-state optimization

Frequently the variables to be controlled are greater in number than those to be manipulated, and not all the variables to be controlled have set-point values, but rather acceptable ranges. There are also **constraints** on the manipulated variables. To take these factors into account, the values of x_s and u_s can be determined by solving a **constrained optimum problem**.

$$\min_{u_s, x_s, \underline{\varepsilon}, \bar{\varepsilon}} \left(\bar{q}^t \bar{\varepsilon} + \underline{q}^t \underline{\varepsilon} + r^t u_s \right)$$

$$x_s = A x_s + B u_s$$

$$u_{\min} \le u_s \le u_{\max}$$

$$y_{\min} - \underline{\varepsilon} \le C x_s + p_k \le y_{\max} + \bar{\varepsilon}$$

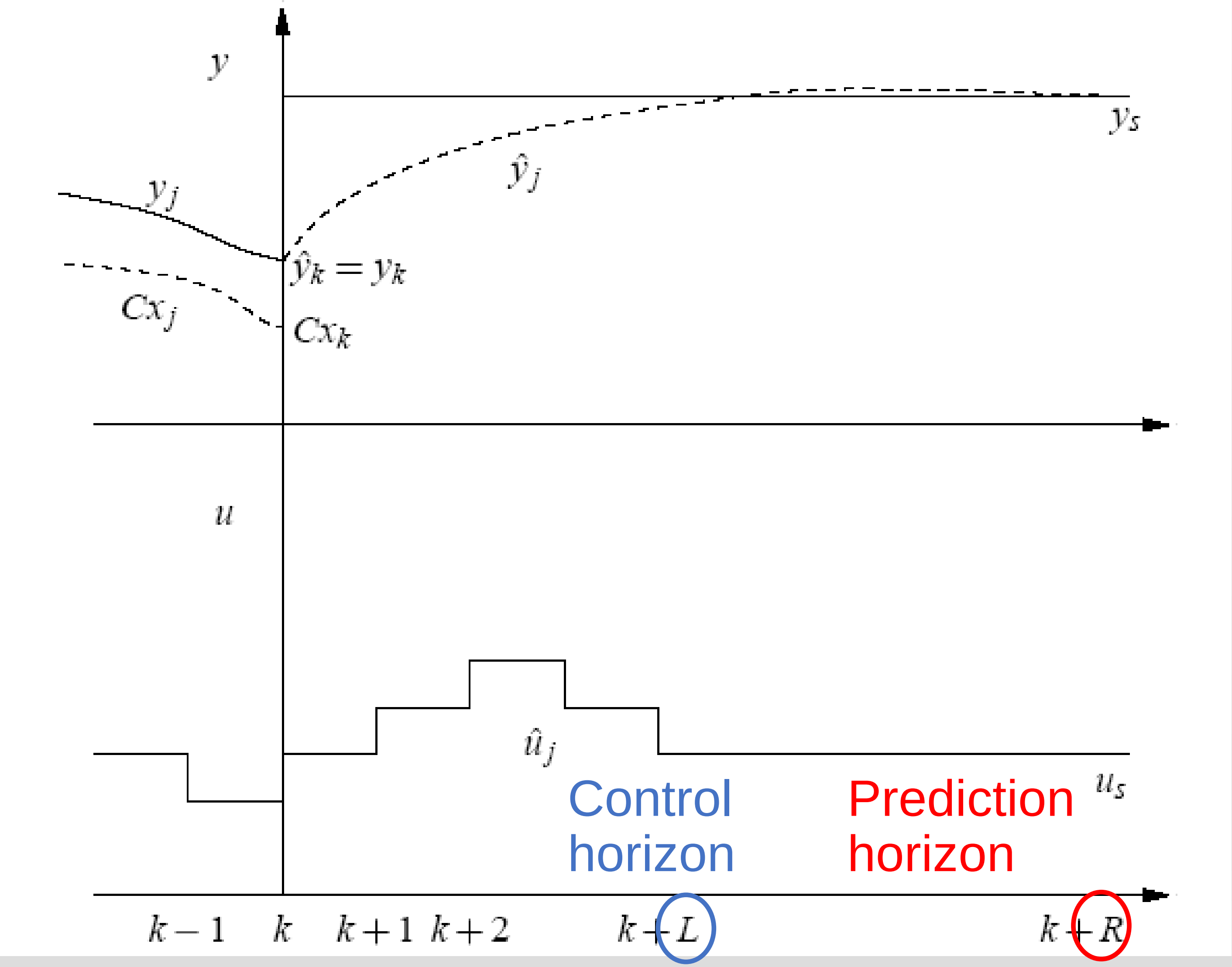
$$\underline{\varepsilon} \ge 0, \; \bar{\varepsilon} \ge 0$$

Equal concern error

Hard-constraints

Soft-constraints

Dynamic optimization



Dynamic optimization

$$\min_{\{u_j\},\{\underline{\varepsilon}_j\},\{\bar{\varepsilon}_j\}} \sum_{j=k}^{k+R} \left\{ \left(\hat{y}_j - y_S\right)^t Q \left(\hat{y}_j - y_S\right) + \Delta\hat{u}_j^t S \Delta\hat{u}_j + \bar{\varepsilon}_j^t \bar{Q} \bar{\varepsilon}_j + \underline{\varepsilon}_j^t \underline{Q} \underline{\varepsilon}_j \right\}$$

$$x_{j+1} = Ax_j + Bu_j$$

$$\hat{y}_j = Cx_j + p_k$$

$$\hat{u}_j = u_s \quad j \geq k + L$$

$$u_{\min} \leq \hat{u}_j \leq u_{\max}$$

$$-\Delta u_{\max} \leq \Delta\hat{u}_j = \hat{u}_j - \hat{u}_{j-1} \leq \Delta u_{\max}$$

$$y_{\min} - \underline{\varepsilon}_j \leq \hat{y}_j \leq y_{\max} + \bar{\varepsilon}_j$$

$$\underline{\varepsilon}_j \geq 0,\ \bar{\varepsilon}_j \geq 0$$

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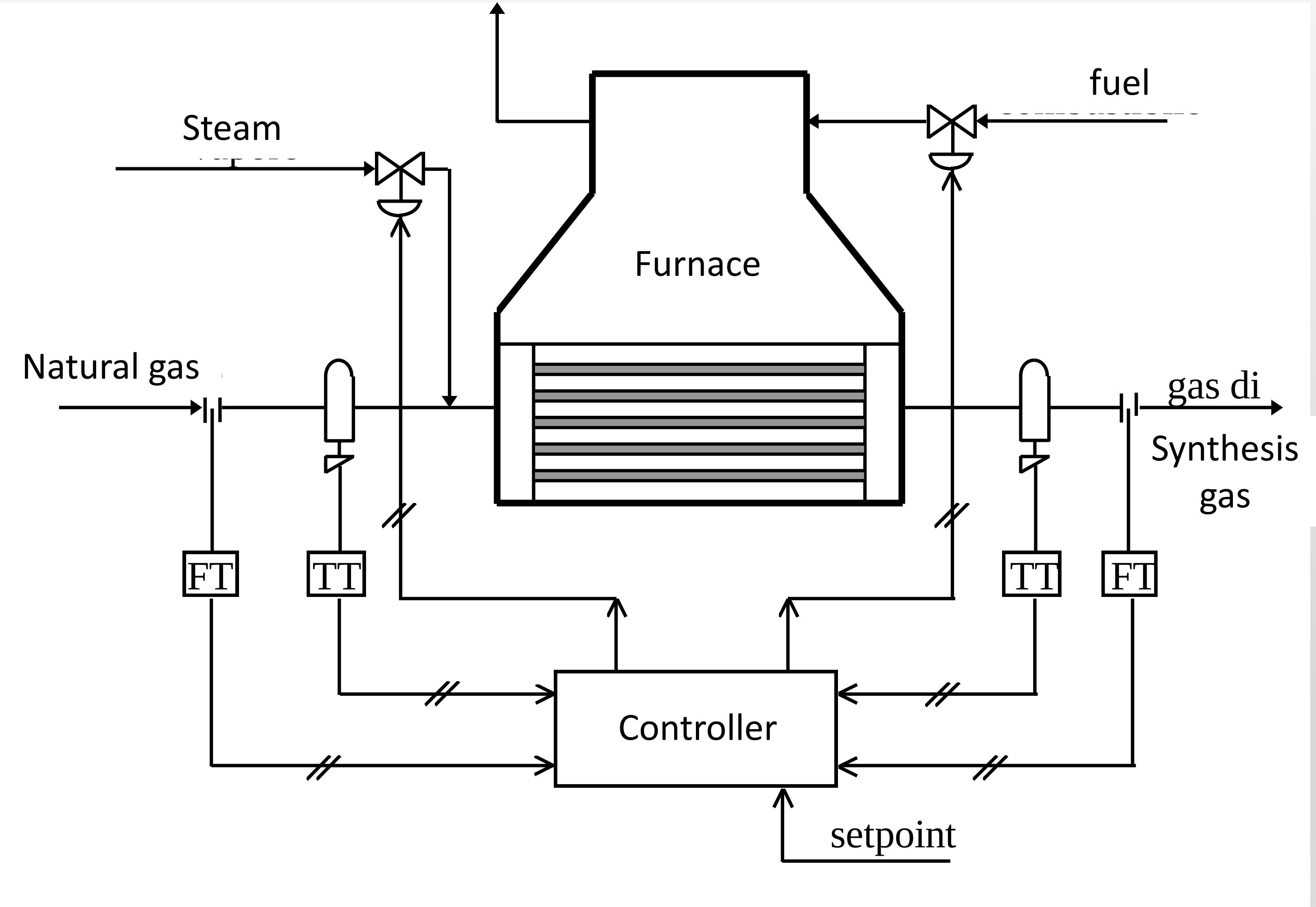
MPC: pros & cons

A MPC may “easily” handle:

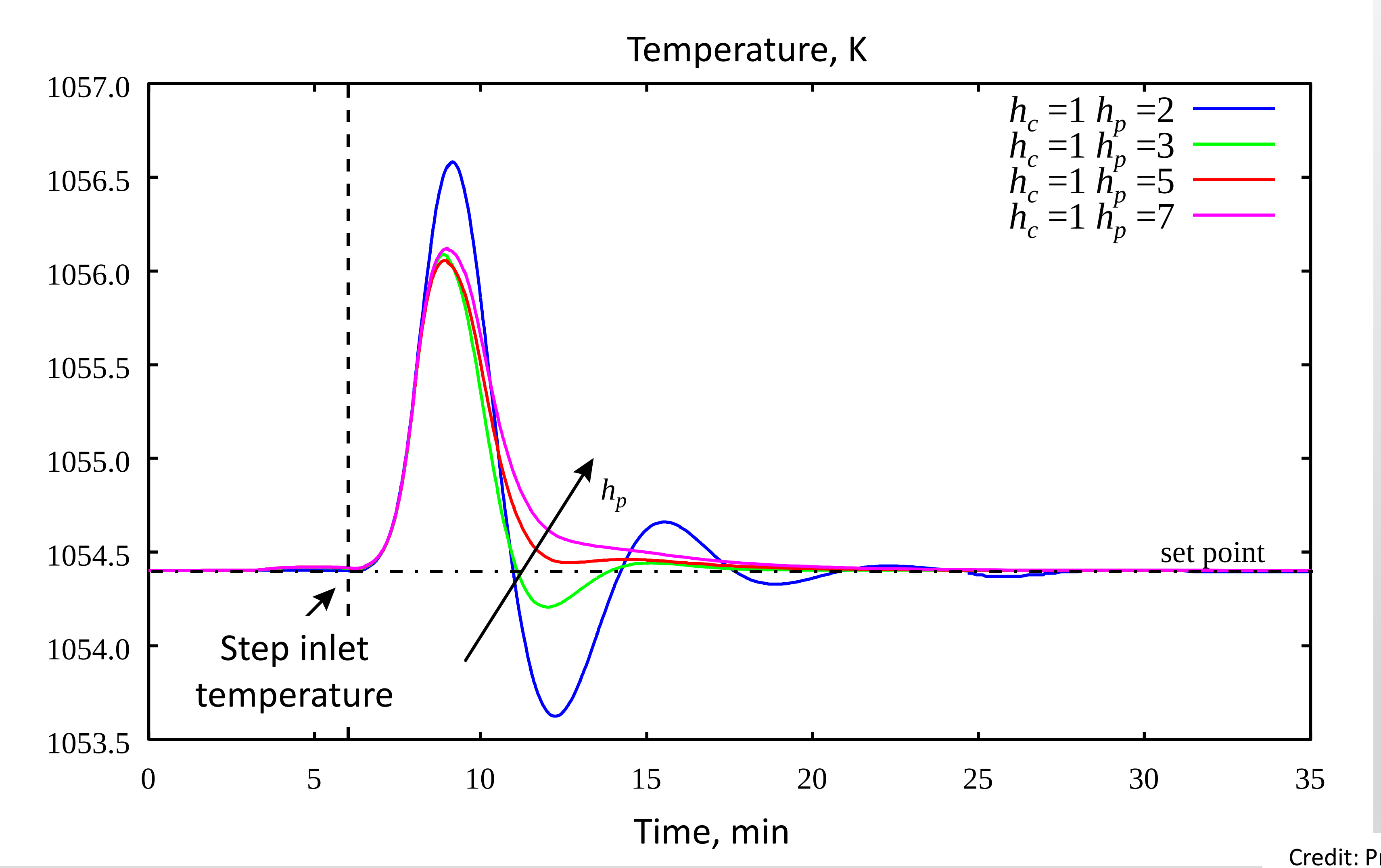
- Multivariate systems
- Measurable and non-measurable disturbances
- Complex dynamics (e. g. time delay, inverse response, instability, non-linearity)
- Constraints (on input/output variables, changing rates of input variables, …)

Example



Credit: Prof. D. Manca

Example



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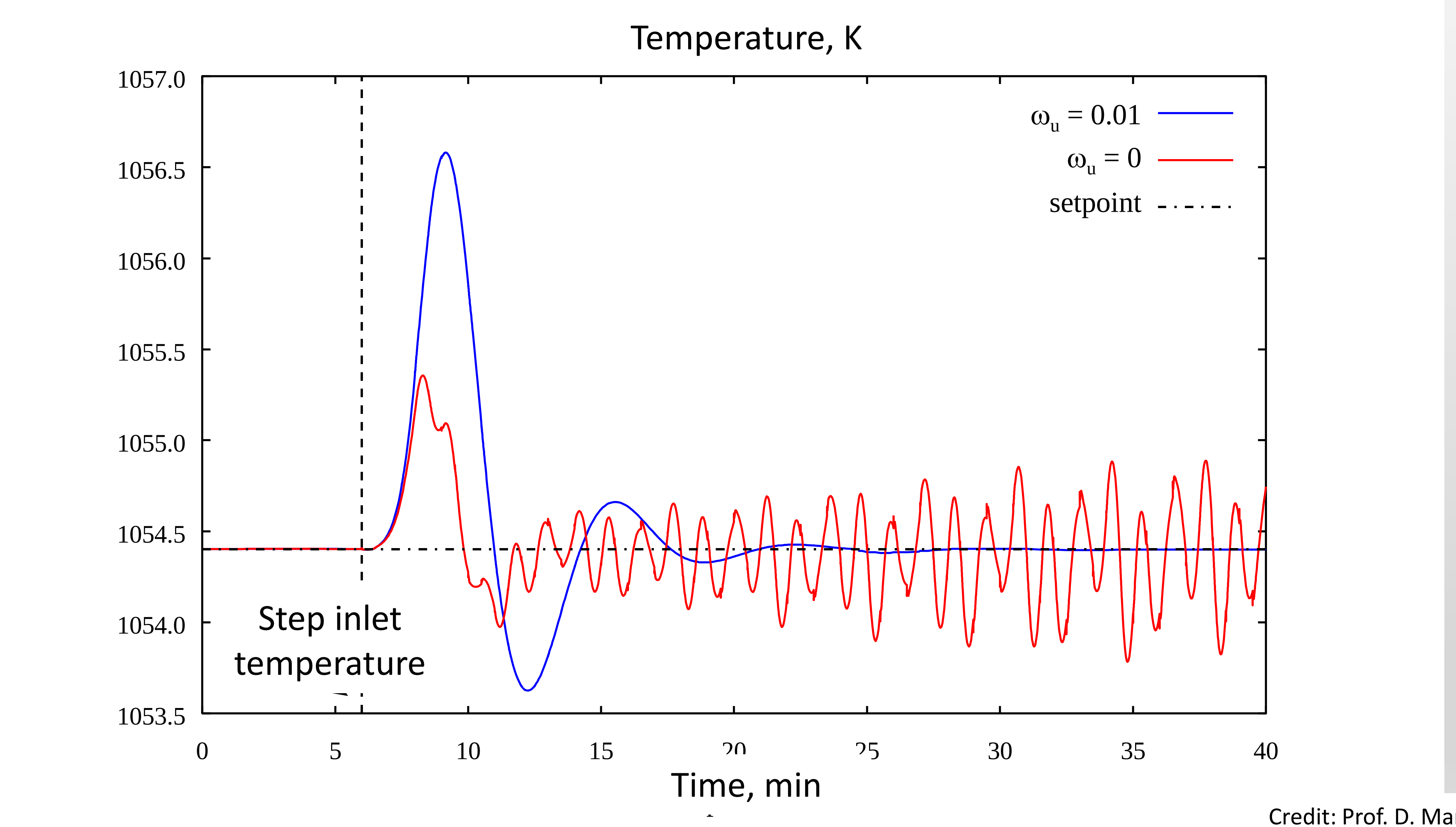
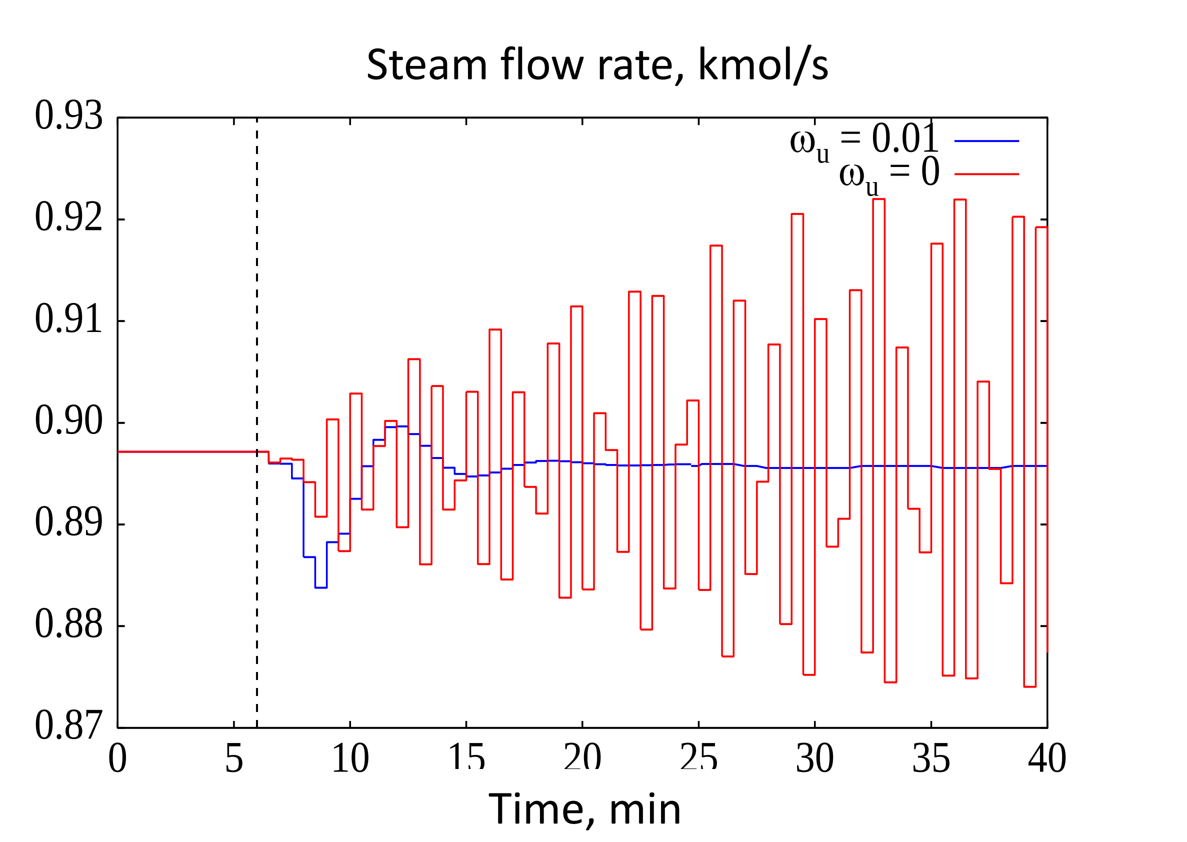
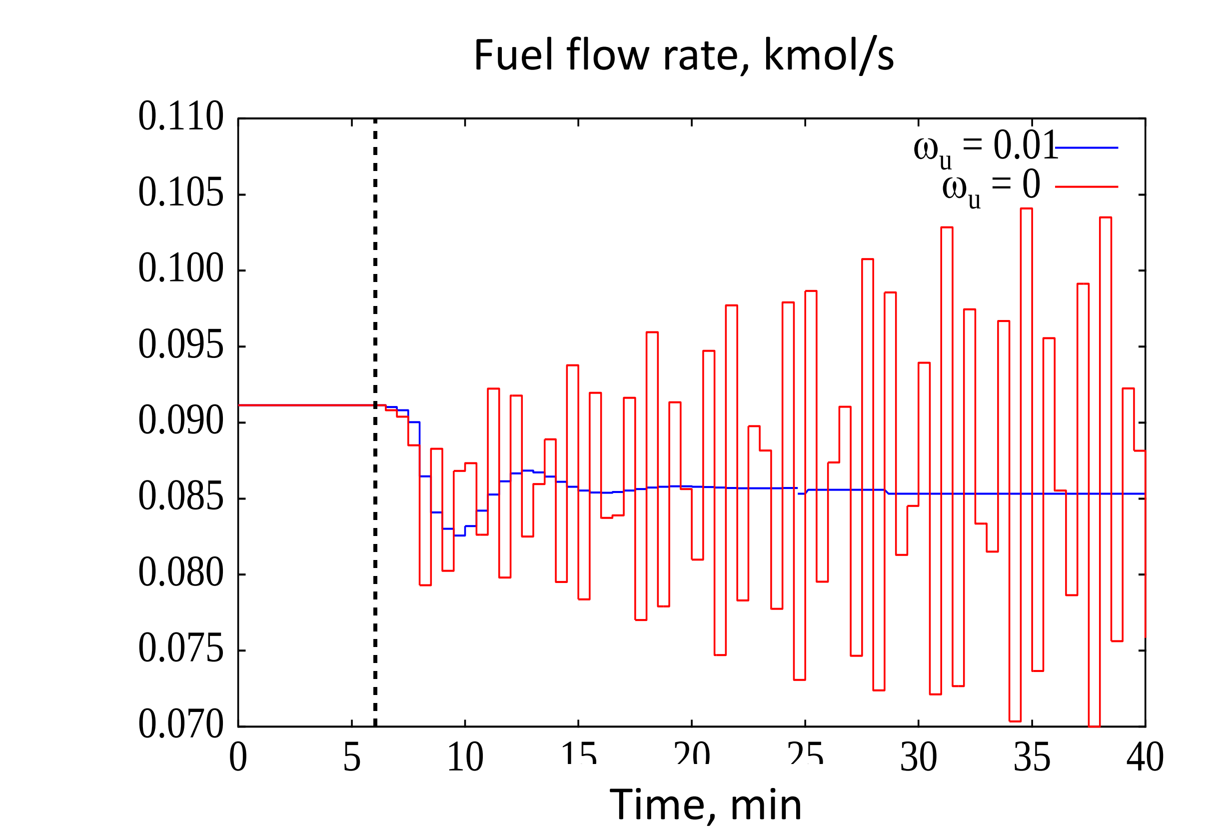
Example



Credit: Prof. D. Manca

Example





Credit: Prof. D. Manca

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