

# MODEL PREDICTIVE CONTROL

## STATE OF THE ART AND POSSIBLE OPPORTUNITIES FOR LIFE-SUPPORT SYSTEMS

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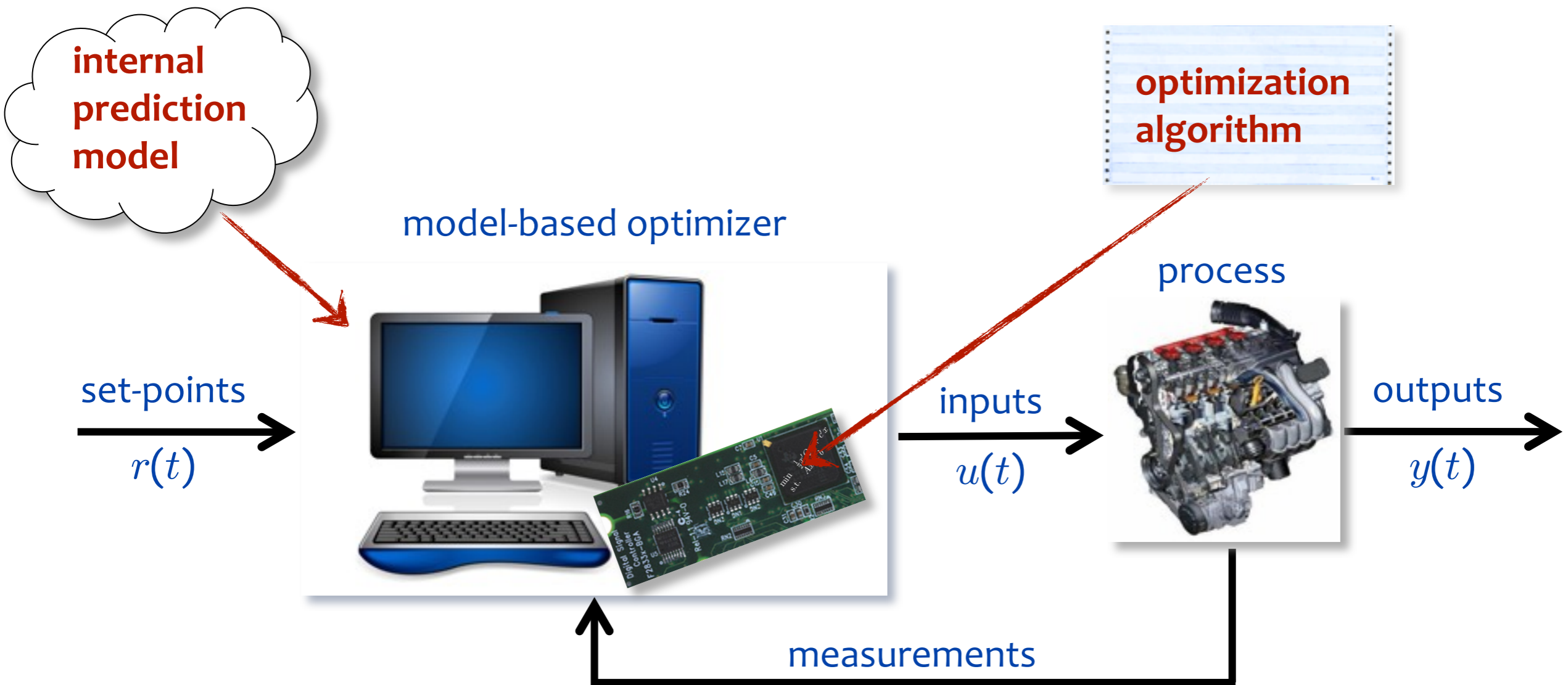
[www.odys.it](http://www.odys.it)



Melissa Workshop - Lausanne, June 8-9, 2016



# MODEL PREDICTIVE CONTROL (MPC)



*simplified*

*Likely*

Use a dynamical **model** of the process to **predict** its future evolution and choose the “best” **control** action

# MODEL PREDICTIVE CONTROL (MPC)

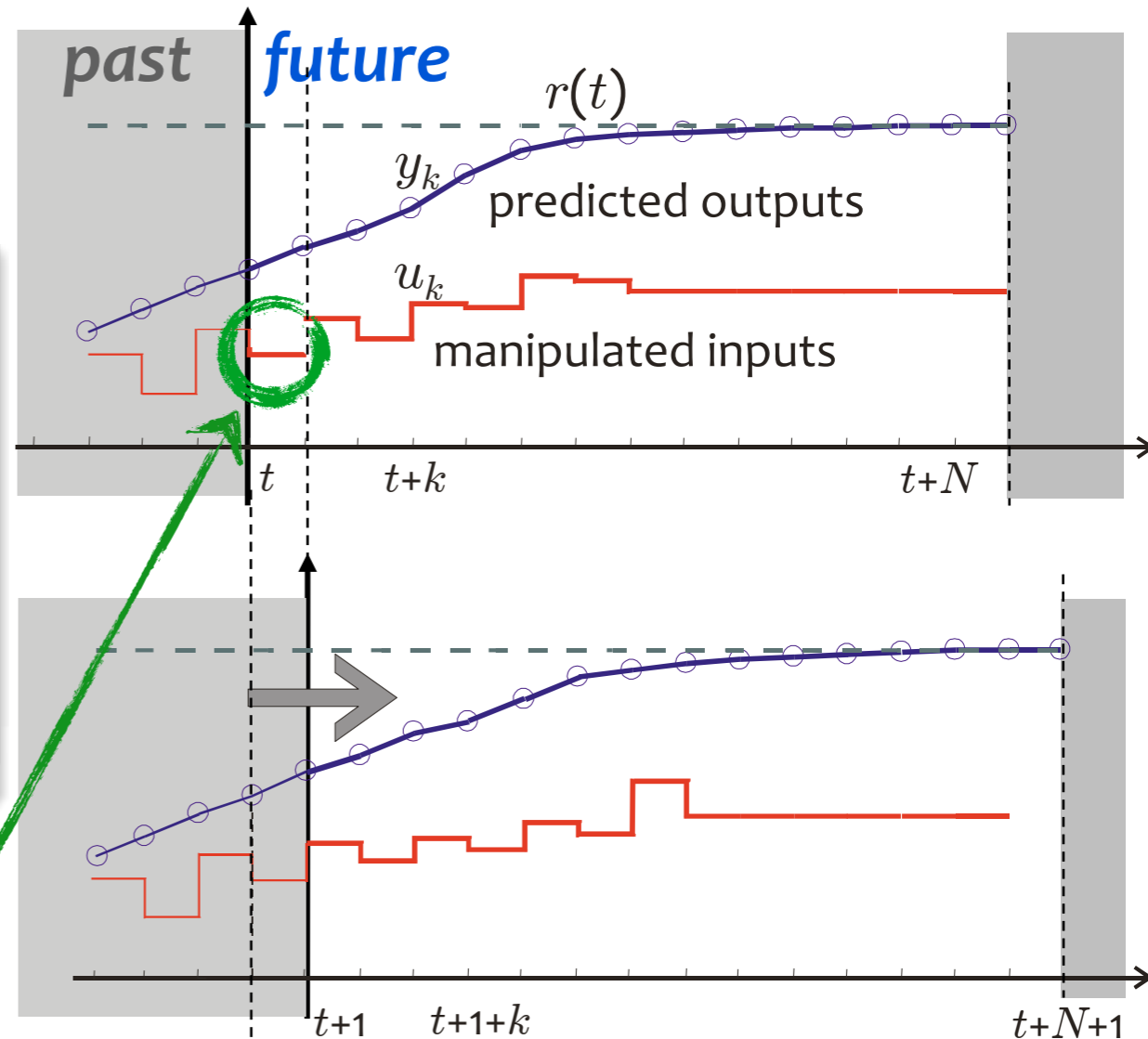
- At each time  $t$ , find the best control sequence over a future horizon of  $N$  steps

penalty on tracking error

penalty on actuation

$$\begin{aligned} \min \quad & \sum_{k=0}^{N-1} \|W^y(y_k - r(t))\|^2 + \|W^u(u_k - u^{\text{ref}}(t))\|^2 \\ \text{s.t.} \quad & x_{k+1} = f(x_k, u_k, t) \\ & y_k = g(x_k, u_k, t) \\ & \text{constraints on } u_k, y_k \\ & x_0 = x(t) \quad \leftarrow \text{feedback!} \end{aligned}$$

numerical optimization problem



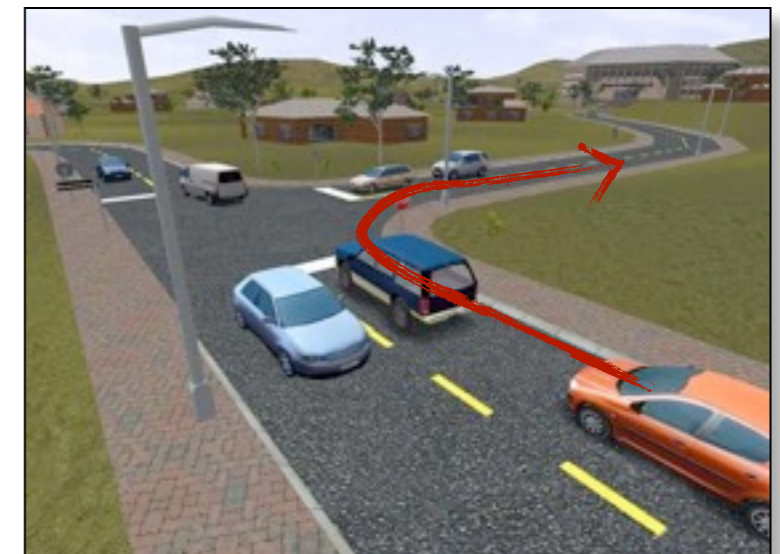
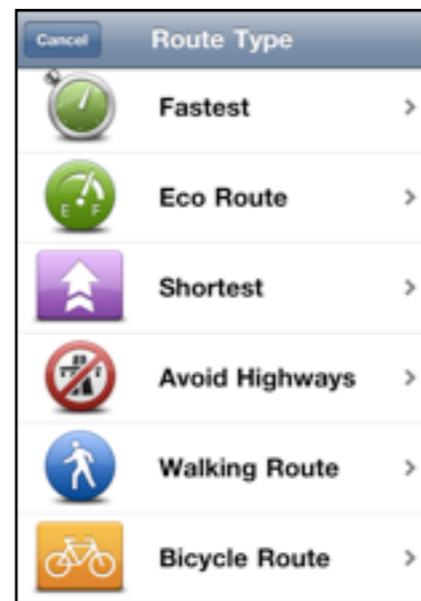
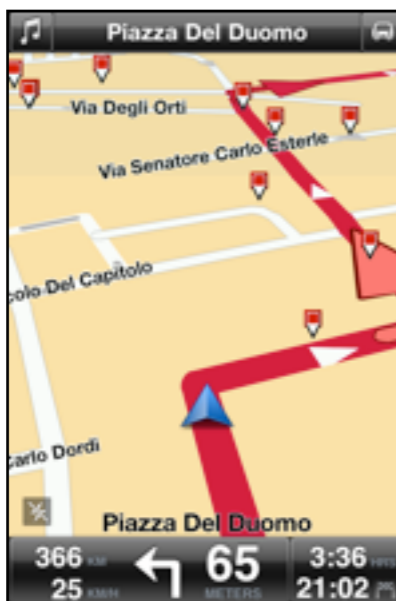
- Only apply the first optimal move  $u(t)$ , throw the rest of the sequence away
- At time  $t+1$ : **Get new measurements, repeat the optimization.** And so on ...

# THE MPC CONCEPT

- MPC is like **playing chess** !

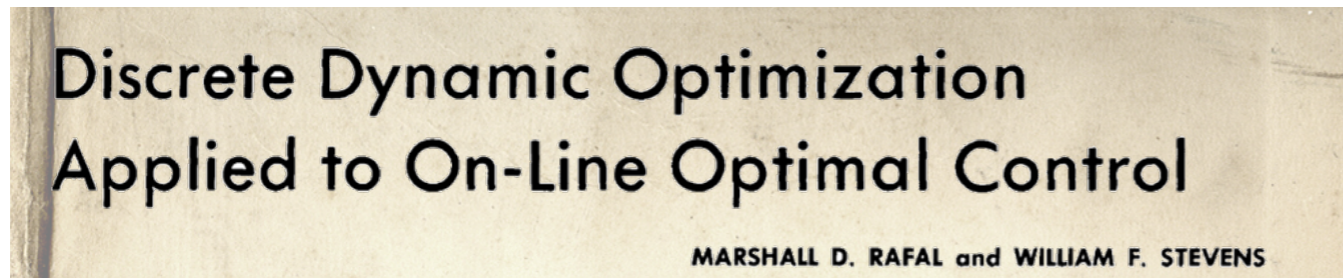


- On-line re-planning while driving:



# MPC IN INDUSTRY

- The idea of using MPC in the process industries dates back to the sixties



(Rafal, Stevens, *AiChE Journal*, 1968)

- MPC used in process industries since the 80's

Area	Aspen Technology	Honeywell Hi-Spec	Adersa <sup>b</sup>	Invensys	SGS <sup>c</sup>	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 & 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
First App.	DMC:1985 IDCOM-M:1987 OPC:1987	PCT:1984 RMPCT:1991	IDCOM:1973 HIECON:1986	1984	1985	
Largest App.	603 × 283	225 × 85	—	31 × 12	—	

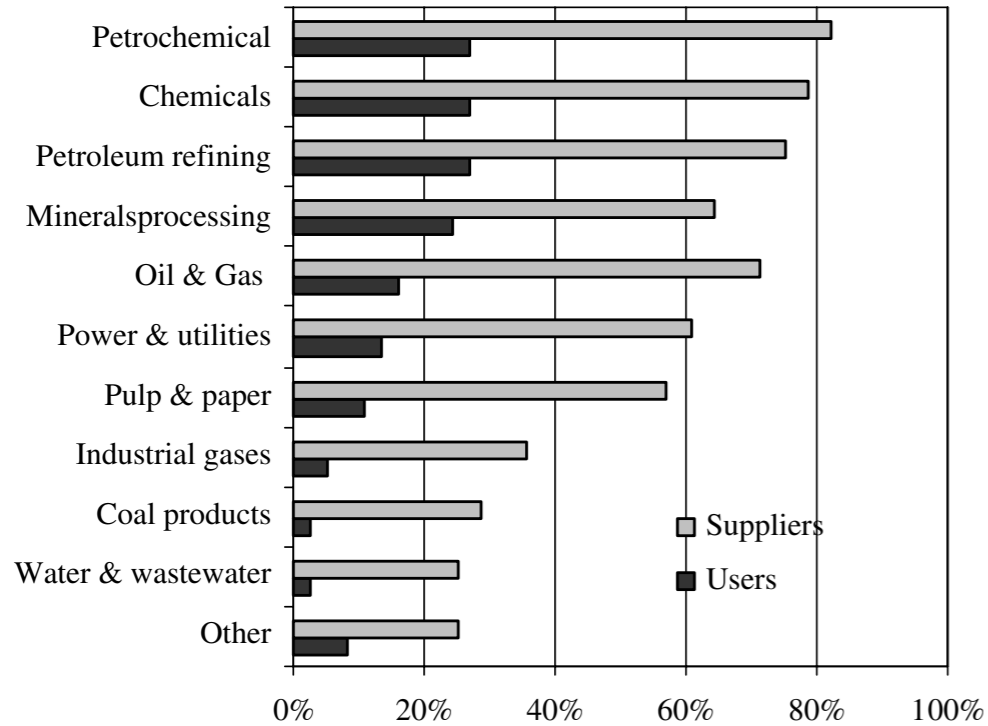
(snapshot survey conducted in mid-1999)

(Qin, Badgewell, 2003)

# MPC IN INDUSTRY

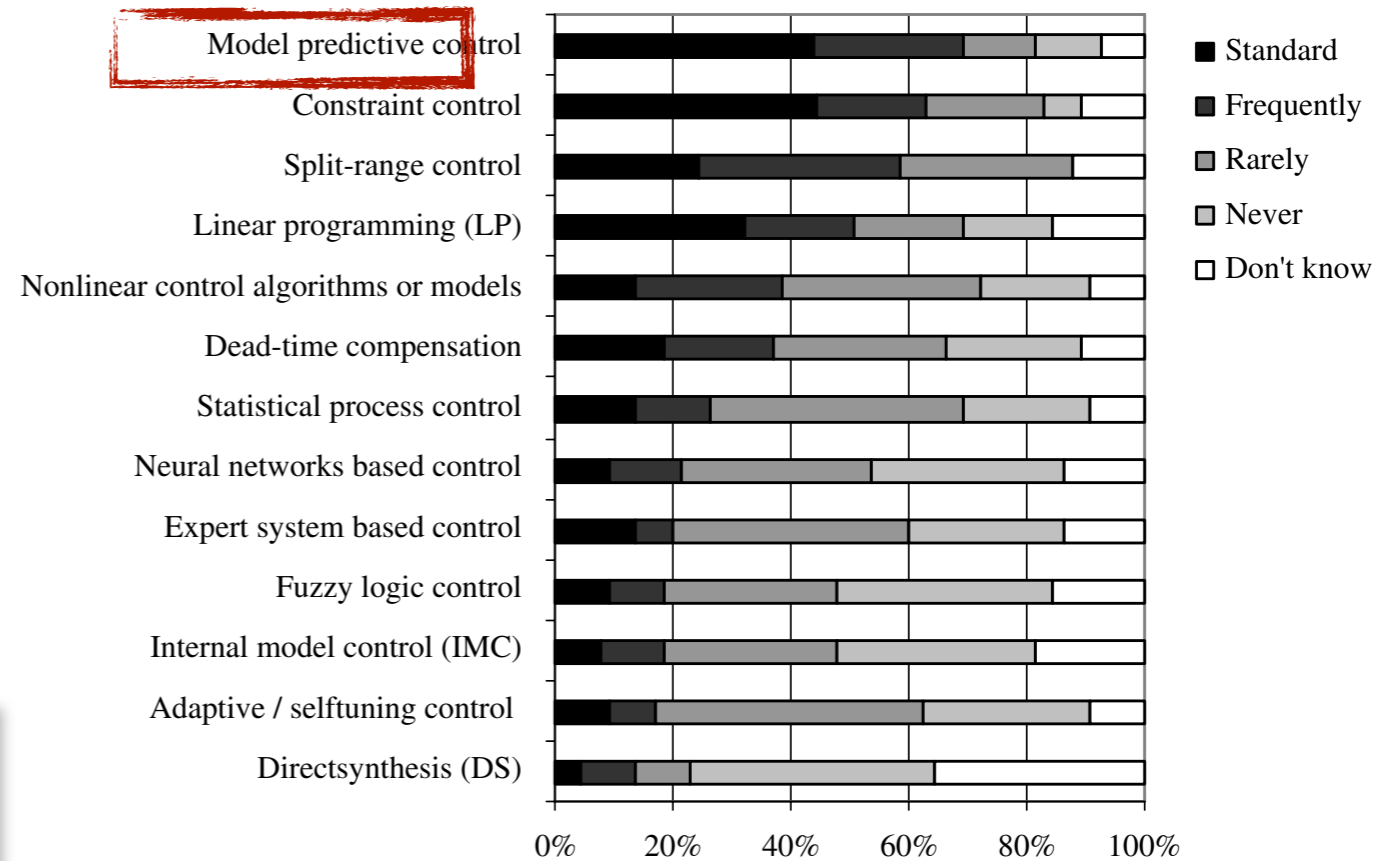
(Bauer & Craig, 2008)

- Economic assessment of Advanced Process Control (APC)



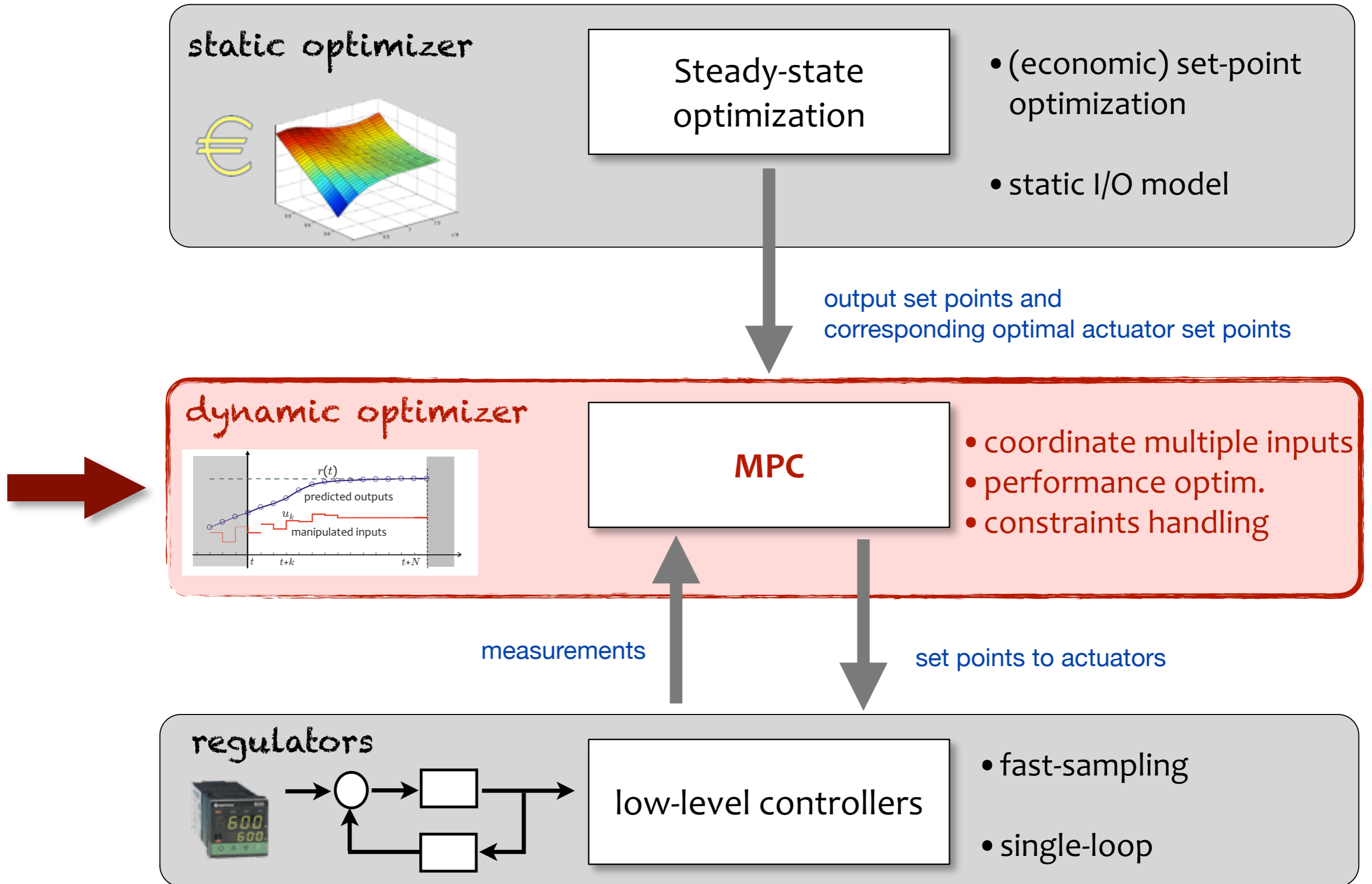
participants of APC survey by industry (worldwide)

**MPC is the *de-facto* standard for advanced control in the process industry.**



Industrial use of APC methods: survey results

# TYPICAL USE OF MPC



# MPC FOR LIFE SUPPORT SYSTEMS

- Quick literature search:

Google

Scholar About **42 results** (0.06 sec)

Google

Scholar About **31 results** (0.02 sec)

- Sherpa Engineering proposed MPC schemes within







# AEROSPACE APPLICATIONS OF MPC



- MPC capabilities explored in new space applications
- New MATLAB MPC Toolboxes developed (**MPCTOOL** and **MPCSoft**)

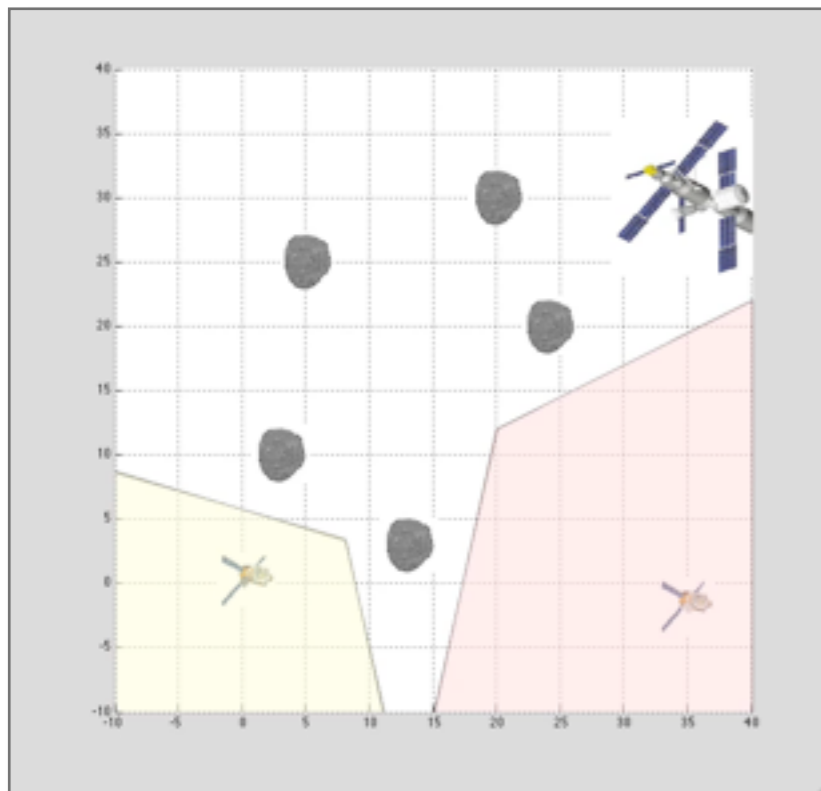
(Bemporad, 2010) (Bemporad, 2012)

powered descent



(Pascucci, Bennani, Bemporad, 2016)

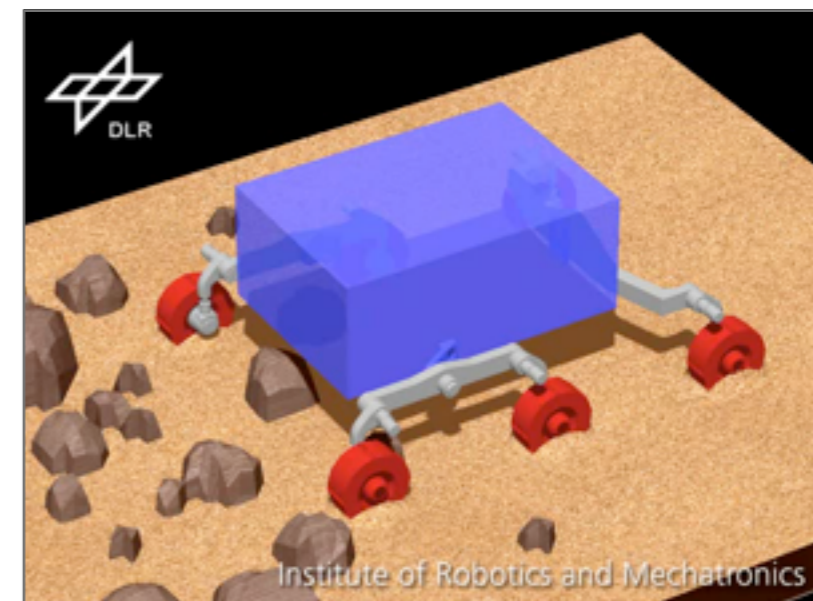
cooperating UAVs



(Bemporad, Rocchi, 2011)

planetary rover

(Krenn et. al., 2012)



# AUTOMOTIVE APPLICATIONS OF MPC

Bemporad, Bernardini, Borrelli, Cimini, Di Cairano, Esen, Giorgetti, Graf-Plessen, Hrovat, Kolmanovsky, Levijoki, Ripaccioli, Trimboli, Tseng, Yanakiev, ... (2001-2016)

## Powertrain

- direct-inj. engine control
- A/F ratio control
- magnetic actuators
- robotized gearbox
- power MGT in HEVs
- cabin heat control in HEVs
- electrical motors

## Vehicle dynamics

- traction control
- active steering
- semiactive suspensions
- autonomous driving

**Ford Motor Company**

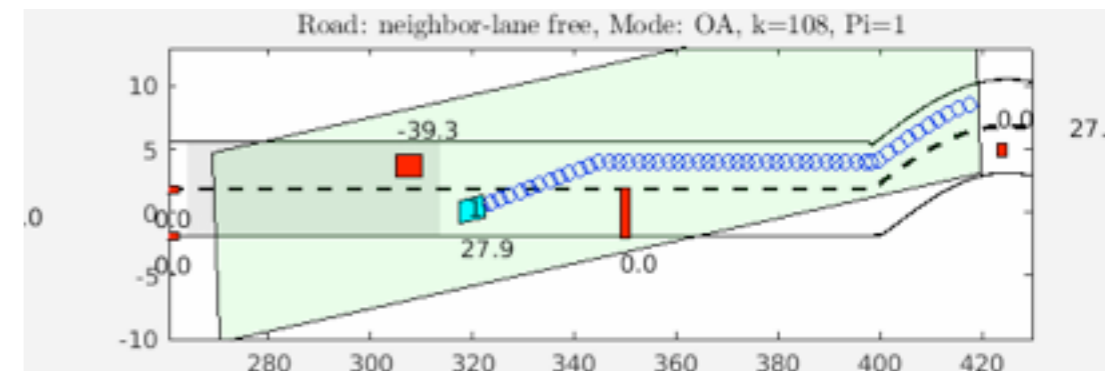
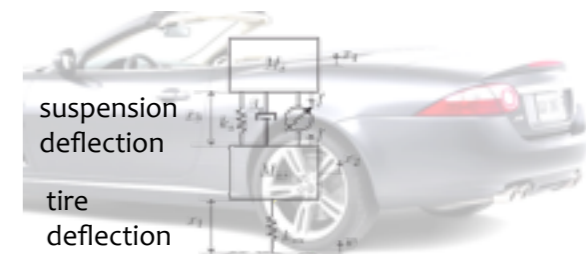
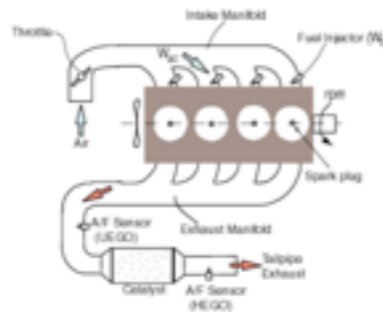
**Jaguar**

**DENSO Automotive**

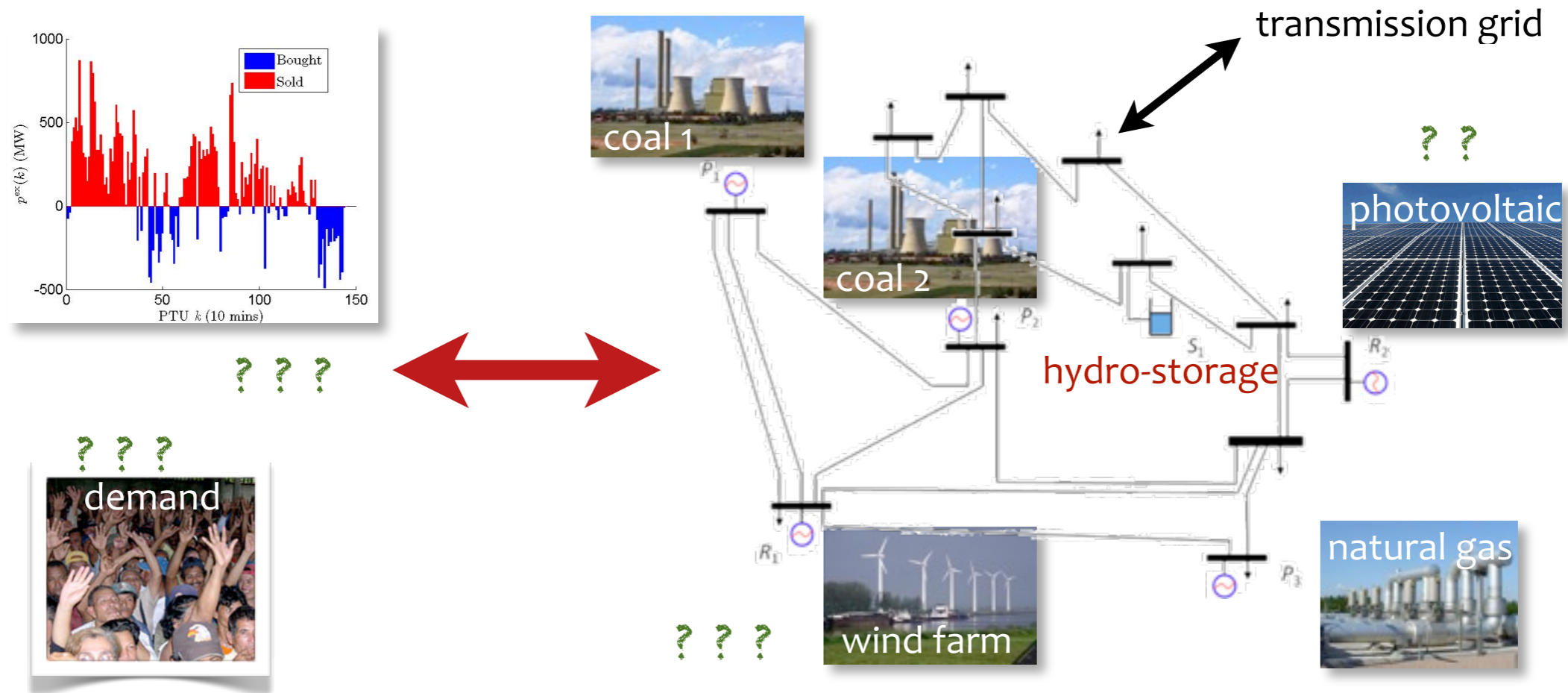
**FIAT**

**General Motors**

**ODY'S**  
Advanced Controls & Optimization



# MPC FOR SMART ELECTRICITY GRIDS



**Dispatch power** in smart distribution grids, **trade energy** on energy markets

**Challenges:** account for **dynamics**, network **topology**, physical **constraints**, and **stochasticity** (of renewable energy, demand, electricity prices)

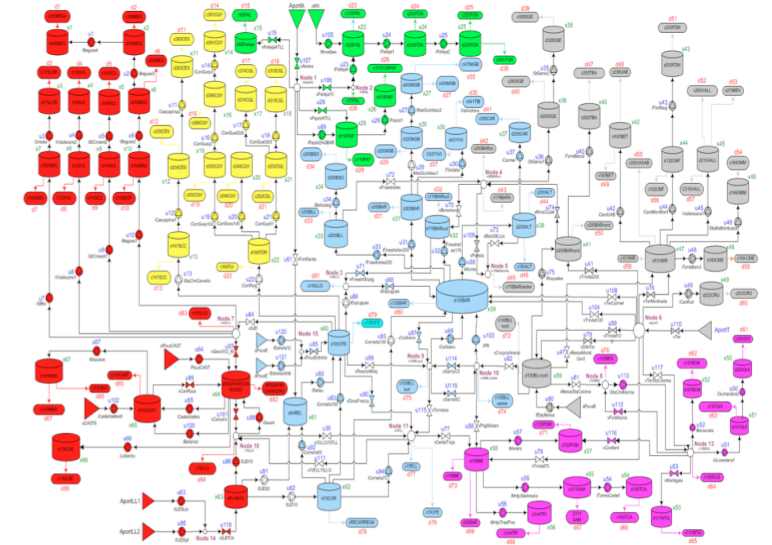
FP7-ICT project “**E-PRICE - Price-based Control of Electrical Power Systems**”  
(2010-2013)



# MPC FOR MANAGEMENT OF DRINKING WATER NETWORKS



Drinking water network of Barcelona:  
81 tanks,  
64 valves  
180 pumps.



Automatically operate a large-scale urban drinking water network

**Challenges:** minimize network's operating costs and ensure demand satisfaction by controlling pumping in real-time, considering storage **dynamics**, **topology**, physical **constraints**, **stochastic** uncertainty (water demand, energy prices)

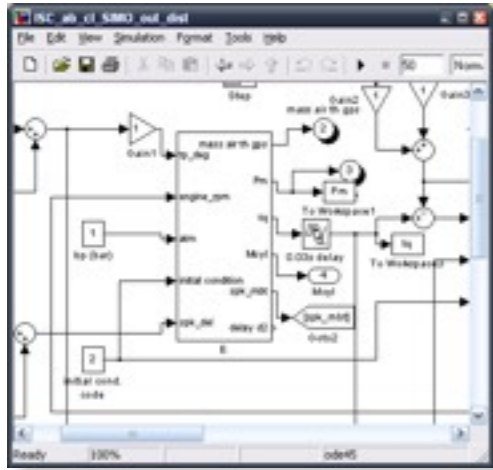
FP7-ICT project “**WIDE** - Decentralized and Wireless Control of Large-Scale Systems”

FP7-ICT project “**EFFINET** - Efficient Integrated RT Monitoring & Control of Drinking Water Nets”

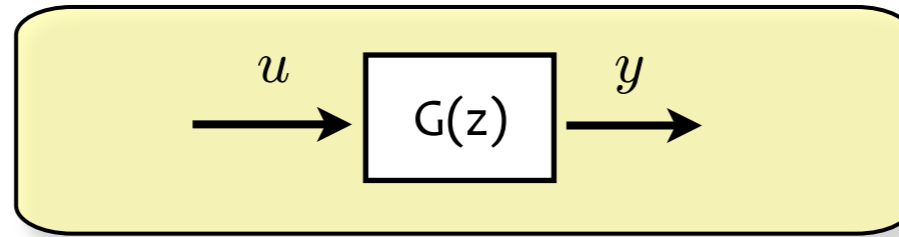


# MPC DESIGN FLOW

High-fidelity simulation model



(simplified) control-oriented prediction model



performance index & constraints

MPC design

closed-loop simulation

physical modeling + parameter estimation

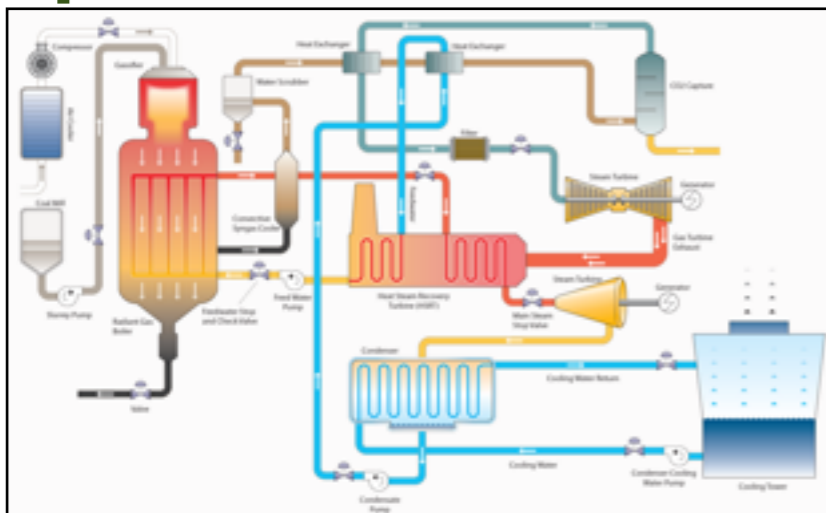
system identification

revise MPC setup

real-time code

```
/* z=A*x0; */  
for (i=0;i<m;i++) {  
    z[i]=A[i]*x[0];  
    for (j=1;j<n;j++) {  
        z[i]+=A[i+m*j]*x[j];  
    }  
}
```

experiments



physical process

# MPC TOOLBOXES

- **MPC Toolbox (The Mathworks, Inc.)**

(Bemporad, Ricker, Morari, 1998-present)

- ▶ Part of Mathworks' official toolbox distribution
- ▶ Great for **education and research**



- **Hybrid Toolbox**

(Bemporad, 2003-present)

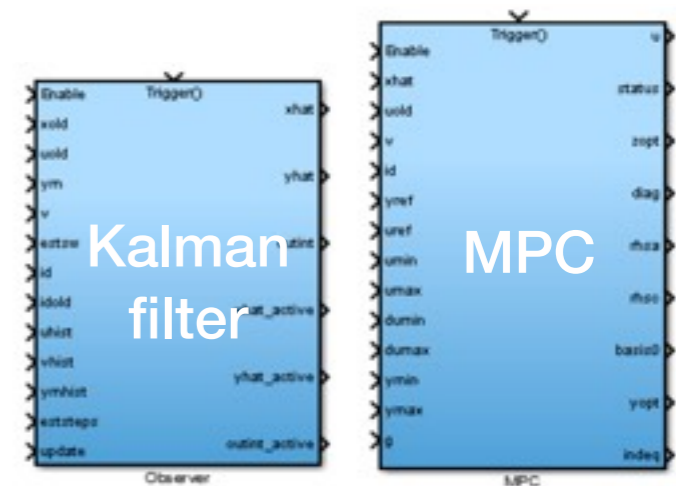
> 6k downloads

- ▶ Free download: <http://cse.lab.imtlucca.it/~bemporad/hybrid/toolbox/>
- ▶ Great for **research and education**

- **ODYS Toolbox**

(Bemporad, Bernardini, 2013-present)

- ▶ Provides flexible and customized MPC control **design** and **seamless integration** in production systems
- ▶ Real-time code written in plain C
- ▶ Designed for production



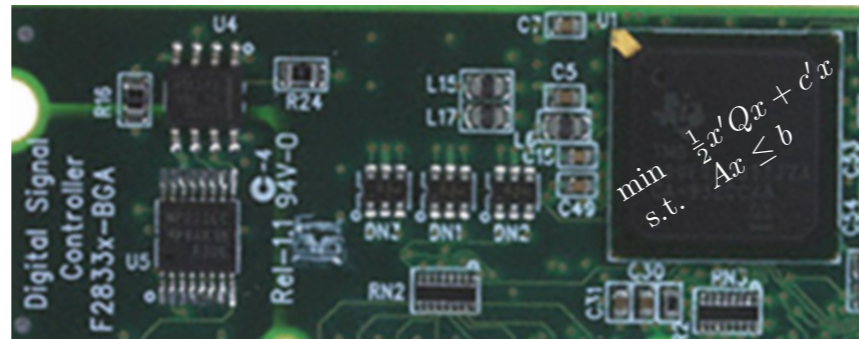
# PROS AND CONS OF MPC

- ✓ Extremely flexible control design approach:
  - Prediction model can be **multivariable**, w/**delays**, **time-varying**, w/ **disturbances**, ...
  - Can exploit available **preview** on future references and measured disturbances
  - Handles **constraints** on inputs and outputs
  - Tuning similar to Linear Quadratic Regulator (**LQR**)
  
- ▶ Price to pay:
  - Requires a (simple) **model** (experiments, systems identification, linearization)
  - Many **degrees of freedom** (weights, horizons, constraints, ...)
  - Requires **real-time computations** to solve the optimization problem



# REQUIREMENTS FOR DEPLOYMENT OF MPC

embedded model-based optimizer



## Requirements:

1. **Speed (throughput)**: solve optimization problem within sampling interval
2. **Robustness** (e.g., with respect to numerical errors)
3. Be able to run on **limited hardware** (e.g., 150 MHz) with **little memory**
4. **Worst-case execution time** must be (tightly) estimated
5. **Code simple** enough to be validated/verified/certified  
(in general, it must be understandable by production engineers)

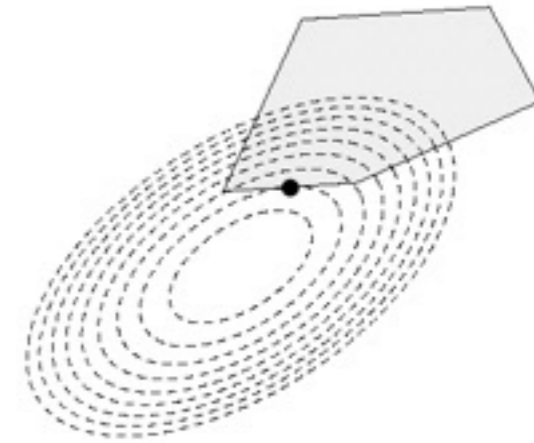


# QUADRATIC PROGRAMMING

- Linear MPC requires solving a **Quadratic Program (QP)**

$$\begin{array}{ll} \min_z & \frac{1}{2} z' H z + x'(t) F' z + \cancel{\frac{1}{2} x'(t) Y x(t)} \\ \text{s.t.} & G z \leq W + S x(t) \end{array}$$

$$z = \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{N-1} \end{bmatrix}$$



- Algorithms for QP have been studied since the 1950's! (Beale, 1955)

A rich set of good QP algorithms is available today, and a lot of research is still going on!

# FAST GRADIENT PROJECTION FOR (DUAL) QP

(Patrinos, Bemporad, IEEE TAC, 2014)

- Main on-line operations involve only **simple linear algebra**

- Convergence rate:

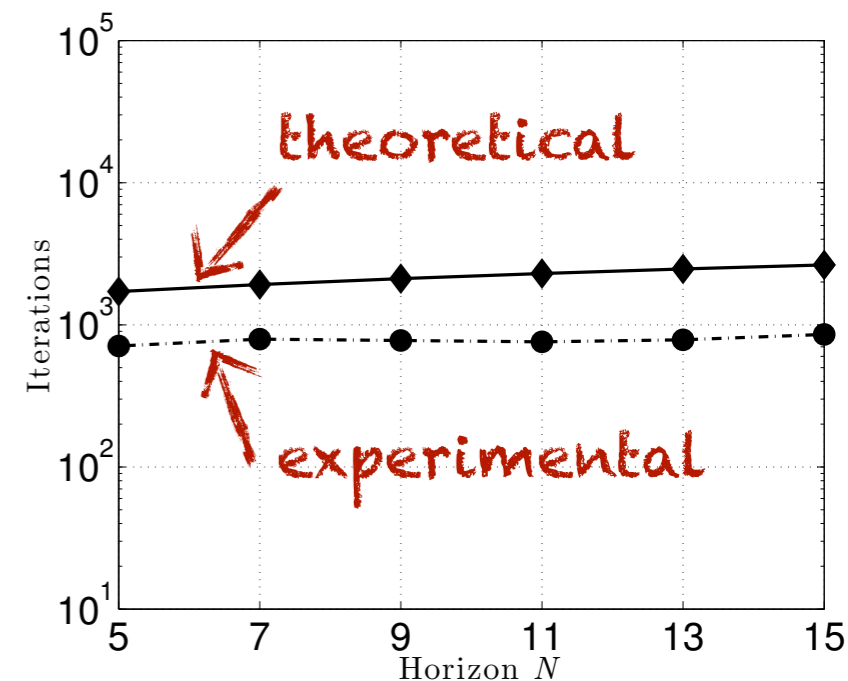
$$f(z_{k+1}) - f^* \leq \frac{2L}{(k+2)^2} \|z_0 - z^*\|^2$$

- Tight bounds on maximum number of iterations

- Can be used to warm-start other methods

- Currently extended to mixed-integer problems

```
while keepgoing && (i<maxiter),  
  
    beta=(i-1)/(i-2).*(i>0);  
  
    w=y+beta*(y-y0);  
    z=-(iMG*w+iMc);  
    s=GLz-bL;  
  
    y0=y;  
  
    % Check termination conditions  
    if all(s<=epsGL),  
        gapL=-w'*s;  
        if gapL<=epsVL,  
            return  
        end  
    end  
  
    y=max(w+s,0);  
  
    i=i+1;  
end
```

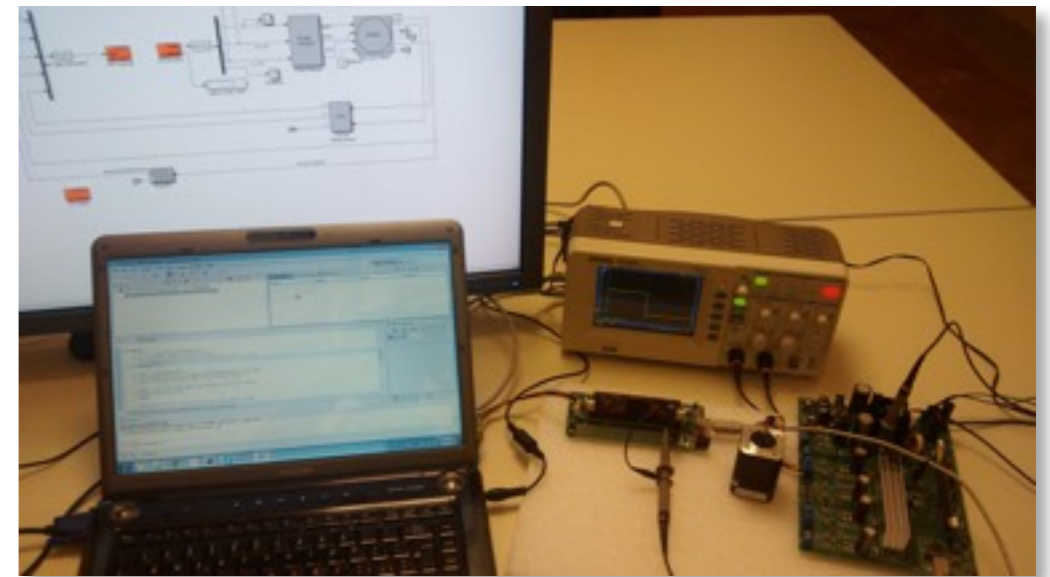


(Naik, Bemporad, work in progress)

# EXPERIMENTS WITH EMBEDDED QP

## TMS320F28335 controlCARD (Real-time Control Applications)

- 32-bit Floating Point (IEEE-754);
- 150MHz clock;
- 68KB Ram / 512KB Flash.



var × constr.	GPAD	AS	ADMM	FBN
4 × 16	332 $\mu$ s (18)	120 $\mu$ s (3)	1.42 ms (62)	208 $\mu$ s (2)
8 × 24	1.1 ms (22)	446 $\mu$ s (5)	4 ms (77)	396 $\mu$ s (2)
12 × 32	2.59 ms (27)	1.19 ms (7)	8.25 ms (82)	652 $\mu$ s (2)*

- **Active set (AS)** methods are usually the best on small problems:
  - excellent quality solutions within few iterations
  - less sensitive to preconditioning (= behavior is more predictable)
  - no need for advanced linear algebra packages

\* GPAD = Dual Accelerated Gradient Projection

(Patrinos, Bemporad, 2014)

\* FBN = Forward-Backwards Netwon (proximal method)

(Patrinos, Guiggiani, Bemporad, 2014)

\* ADMM = Alternating Directions Method of Multipliers

(Boyd et al., 2010)

# MPC IN FINITE-PRECISION ARITHMETICS

(Patrinos, Guiggiani, Bemporad, 2013)

- Gradient projection works in fixed-point arithmetics

$$\max_i g_i(z_k) \leq \frac{2LD^2}{k+1} + L_v \epsilon_z^2 + 4D\epsilon_\xi$$

exponentially decreasing with number  $p$  of fractional bits

max constraint violation

Table 1  
Fixed-point hardware implementation

Size [variables/constraints]	Time [ms]	Time per iteration [ $\mu$ s]	Code Size [KB]
10/20	22.9	226	15
20/40	52.9	867	17
40/80	544.9	3382	27
60/120	1519.8	7561	43

Table 2  
Floating-point hardware implementation

Size [variables/constraints]	Time [ms]	Time per iteration [ $\mu$ s]	Code Size [KB]
10/20	88.6	974	16
20/40	220.1	3608	21
40/80	2240	13099	40
60/120	5816	30450	73



32-bit Atmel SAM3X8E  
ARM Cortex-M3 processing unit  
84 MHz, 512 KB of flash memory and 100 KB of RAM

fixed-point about 4x faster than floating-point

# LINEAR PARAMETER-VARYING (LPV) MPC

linear prediction model

$$\begin{cases} x_{k+1} = A(p(t))x_k + B_u(p(t))u_k + B_v(p(t))v_k \\ y_k = C(p(t))x_k + D_v(p(t))v_k \end{cases} \quad x_0 = x(t)$$

- Weights, horizon, constraints can all depend on current parameter  $p(t)$



$$\begin{aligned} \min_U & \quad \frac{1}{2}U'H(p(t))U + x'(t)F(p(t))'U \\ \text{s.t.} & \quad G(p(t))U \leq W(p(t)) + S(p(t))x(t) \end{aligned}$$

**(convex) Quadratic Program (QP)**

All QP matrices must be constructed on line

- Can be extended to LTV (Linear Time-Varying) prediction models
- LPV/LTV models can be obtained from linearization of nonlinear models or from black-box LPV system identification

# LINEARIZATION AND TIME-DISCRETIZATION

- Model is nonlinear and continuous-time

$$\frac{dx}{dt} = f(x(t), u(t))$$

- Linearization around a nominal state  $\bar{x}(t)$  and input  $\bar{u}(t)$   
(an **equilibrium**, a reference **trajectory**, or the **current** values)

$$\begin{aligned} \frac{dx}{dt}(t + \tau) &\simeq \frac{\partial f}{\partial x} \Big|_{\bar{x}(t), \bar{u}(t)} (x(t + \tau) - \bar{x}(t)) \\ &+ \frac{\partial f}{\partial u} \Big|_{\bar{x}(t), \bar{u}(t)} (u(t + \tau) - \bar{u}(t)) + f(x(t), u(t)) \end{aligned}$$

- Conversion to discrete-time linear prediction model

discrete-time  
LPV model

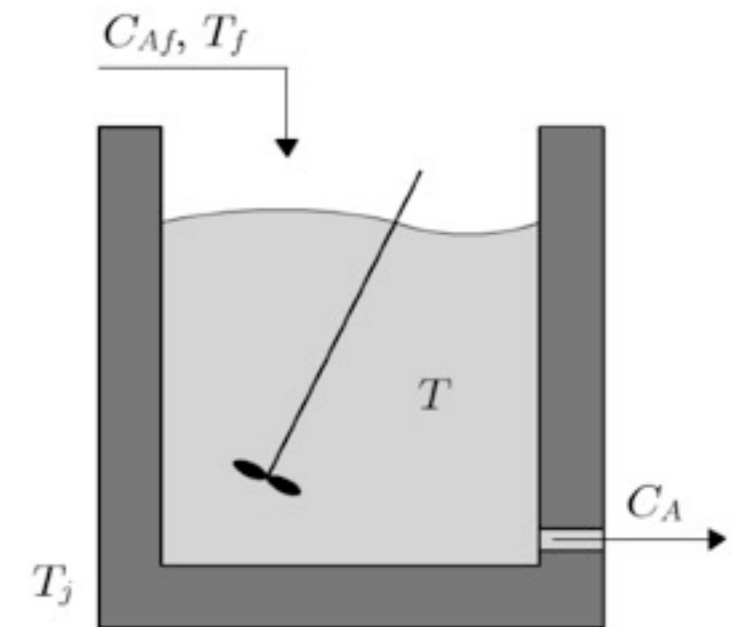
$$x_{k+1} = \overset{A(t)}{\left( I + T_s \frac{\partial f}{\partial x} \Big|_{\bar{x}(t), \bar{u}(t)} \right)} x_k + \overset{B(t)}{\left( T_s \frac{\partial f}{\partial u} \Big|_{\bar{x}(t), \bar{u}(t)} \right)} u_k + \overset{f(t)}{f_k}$$

model matrices  
depend on  
current time  $t$

# EXAMPLE: LTV-MPC OF A NONLINEAR CSTR SYSTEM

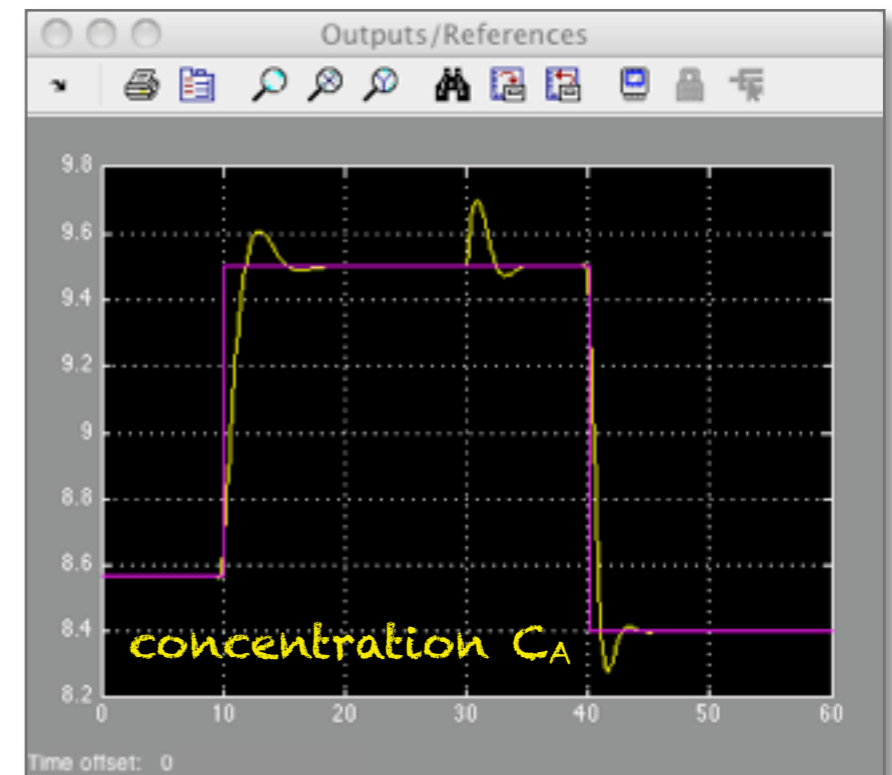
- MPC control of a diabatic continuous stirred tank reactor (CSTR)
- Process model is rather nonlinear:

$$\begin{aligned}\frac{dC_A}{dt} &= \frac{F}{V}(C_{Af} - C_A) - C_A k_0 e^{-\frac{\Delta E}{RT}} \\ \frac{dT}{dt} &= \frac{F}{V}(T_f - T) + \frac{UA}{\rho C_p V}(T_j - T) - \frac{\Delta H}{\rho C_p} C_A k_0 e^{-\frac{\Delta E}{RT}}\end{aligned}$$



- $T$  : temperature inside the reactor [K] (state)
- $C_A$  : concentration of the reagent in the reactor [kgmol/m<sup>3</sup>] (state)
- $T_j$  : jacket temperature [K] (input)
- $T_f$  : feedstream temperature [K] (measured disturbance)
- $C_{Af}$  : feedstream concentration [kgmol/m<sup>3</sup>] (measured disturbance)

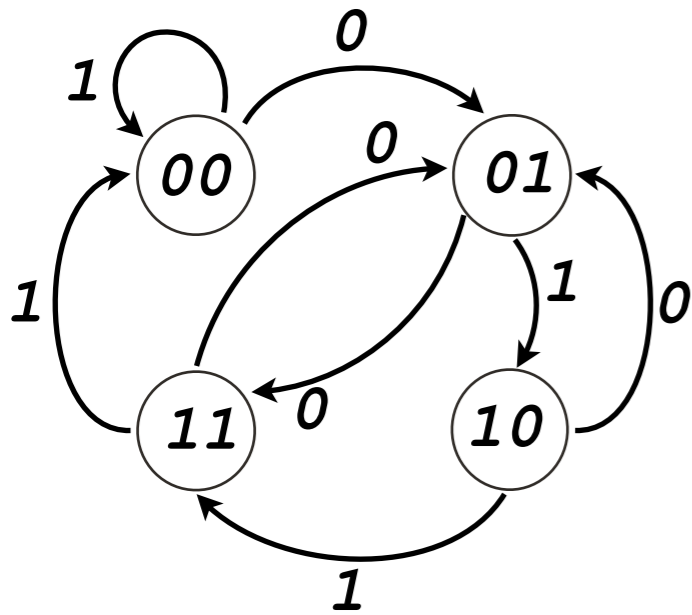
- Objective: manipulate  $T_j$  to regulate  $C_A$  on desired set-point



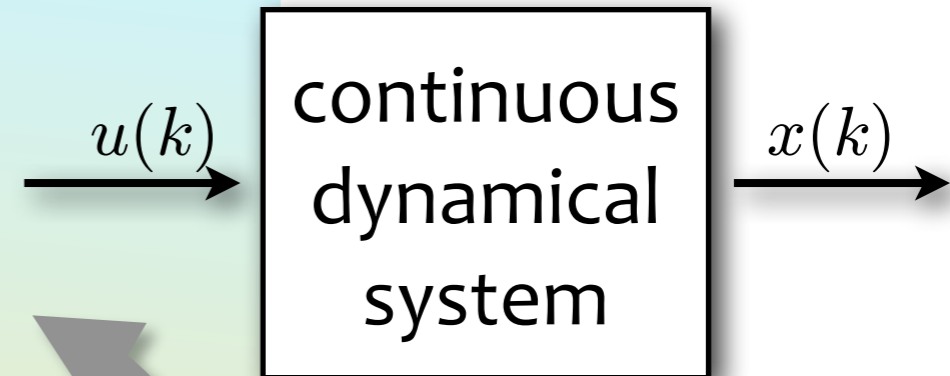


# MODEL PREDICTIVE CONTROL OF HYBRID SYSTEMS

cyber system



physical system



hybrid  
dynamical  
system

- Variables are **discrete-valued**

$$x \in \{0, 1\}^{n_b}, \quad u \in \{0, 1\}^{m_b}$$

- Dynamics = **finite state machine**

- **Logic** constraints, **rules**

- Variables are **real-valued**

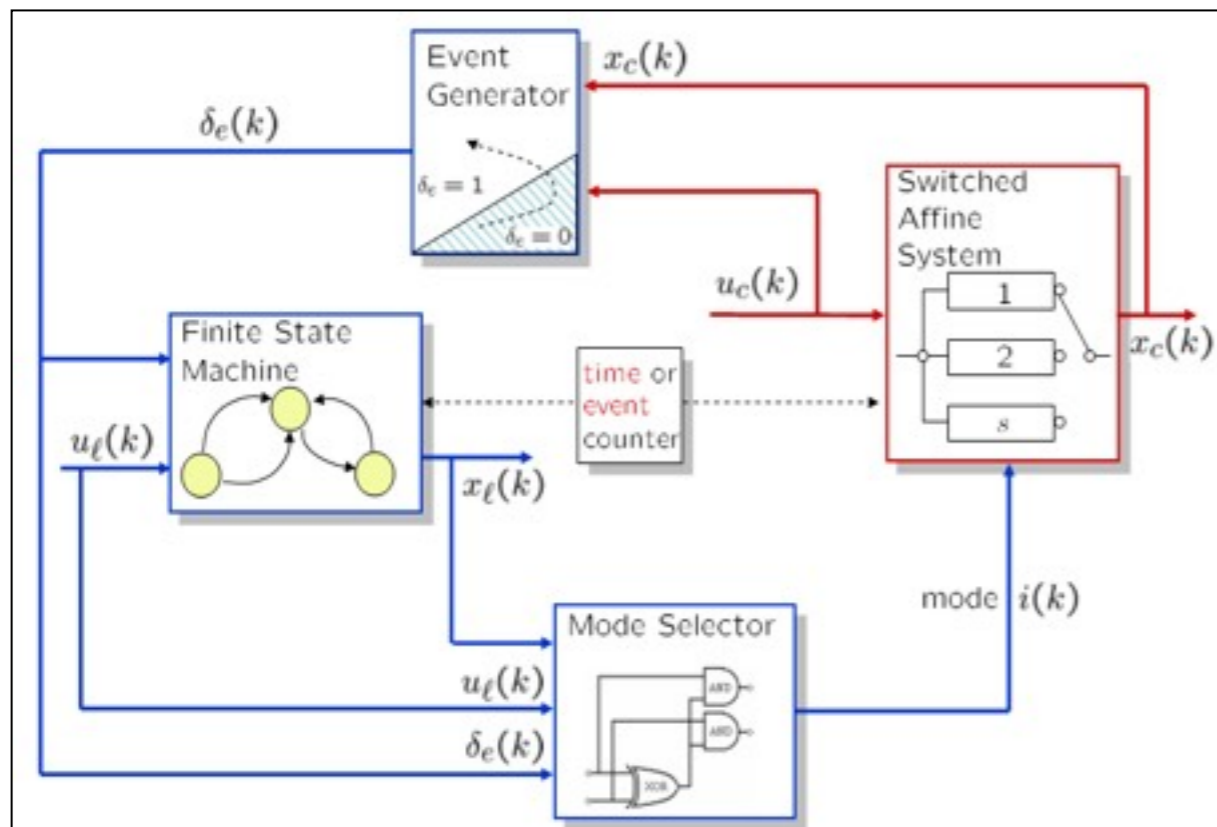
$$x \in \mathbb{R}^{n_c}, \quad u \in \mathbb{R}^{m_c}$$

- **Difference/differential equations**

- **Linear inequality** constraints

# HYBRID MODEL PREDICTIVE CONTROL

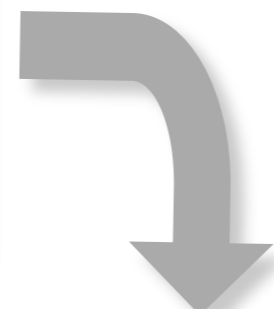
## Discrete Hybrid Automaton (Torrise, Bemporad, 2004)



## Hybrid Toolbox (Bemporad, 2003+)



<http://cse.lab.imtlucca.it/~bemporad/hybrid/toolbox>



## Mixed Logical Dynamical (MLD) systems (Bemporad, Morari 1999)

$$\begin{cases} x_{k+1} = Ax_k + B_1u_k + B_2\delta_k + B_3z_k + B_5 \\ y_k = Cx_k + D_1u_k + D_2\delta_k + D_3z_k + D_5 \\ E_2\delta_k + E_3z_k \leq E_4x_k + E_1u_k + E_5 \end{cases}$$

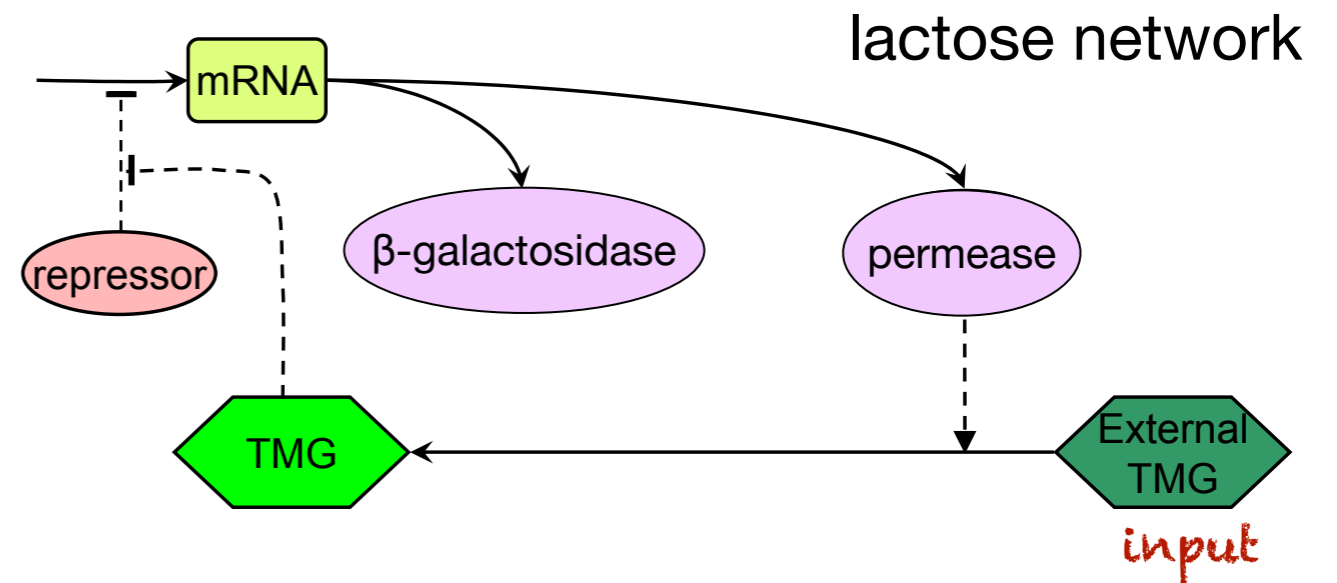
continuous & binary variables

- MPC problem can be solved by **mixed-integer programming (MIP)**
- Excellent public domain/commercial packages exist to solve MIP's

# HYBRID MPC OF INDUCTION OF ESCHERICHIA COLI

(Julius, Sakar, Bemporad, Pappas, 2007)

- **Goal:** control the **lactose regulation system** of a colony of *E. coli*

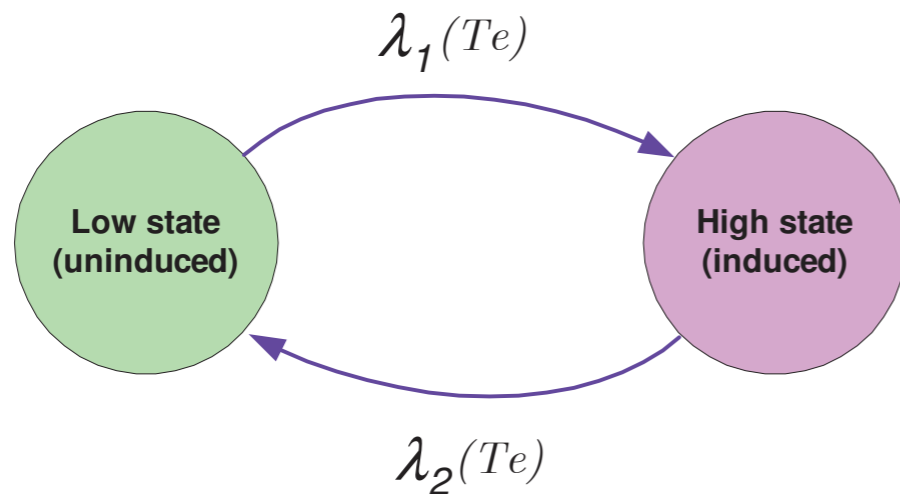


TMG = *thio-methyl galactosidase* concentration

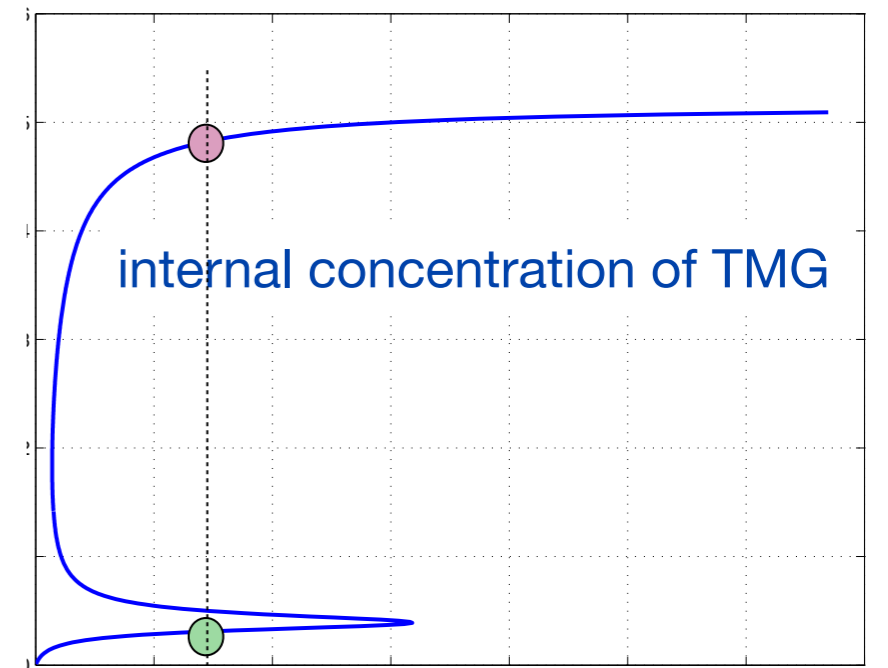
- Model, measurements, and actuation are at the **entire colony** level

# HYBRID MPC OF INDUCTION OF ESCHERICHIA COLI

- **Bistable** lactose regulation system of E. coli



two-state Markov chain



$T_e$  = external concentration of TMG

- The probabilities  $x_{lo}$ ,  $x_{hi}$  to be in low/high state satisfy the dynamics

$$\frac{d}{dt} \begin{bmatrix} x_{lo} \\ x_{hi} \end{bmatrix} = \begin{bmatrix} -\lambda_1(T_e) & \lambda_2(T_e) \\ \lambda_1(T_e) & -\lambda_2(T_e) \end{bmatrix} \begin{bmatrix} x_{lo} \\ x_{hi} \end{bmatrix}$$

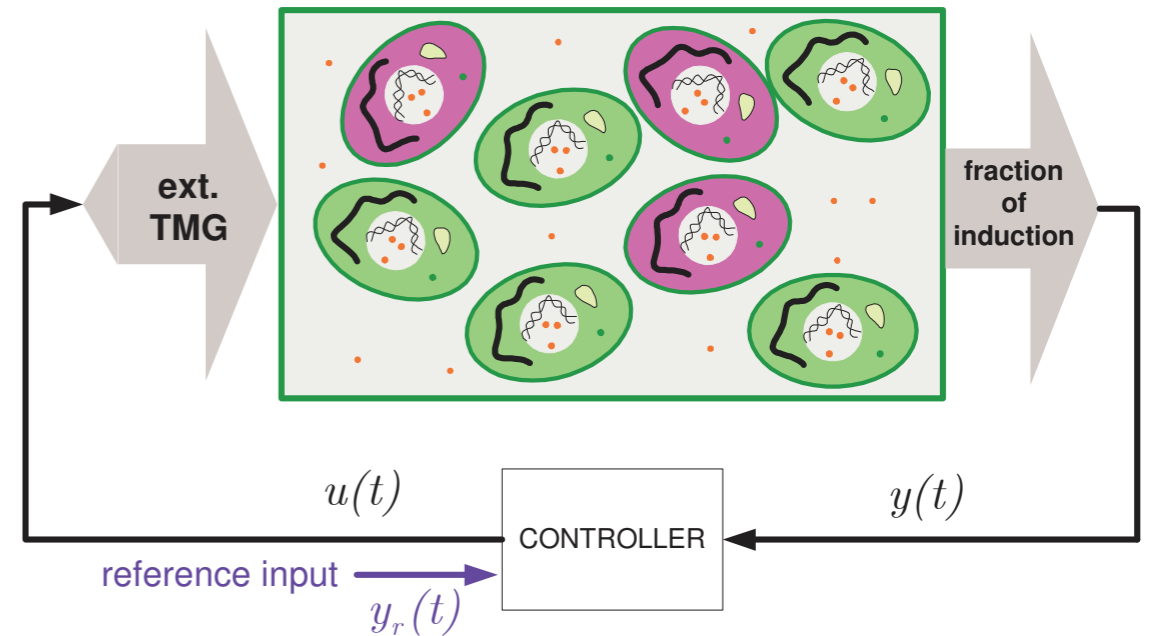
- Transition rates  $\lambda_1$ ,  $\lambda_2$  modeled as **piecewise constant** functions of  $T_e$

$T_e$ [ $10^{-3}$ mM]	$\lambda_1(T_e)$ [ $\text{min}^{-1}$ ]	$\lambda_2(T_e)$ [ $\text{min}^{-1}$ ]
[1.4, 1.5)	$8.68 \cdot 10^{-4}$	$5.91 \cdot 10^{-3}$
[1.5, 1.6)	$9.27 \cdot 10^{-4}$	$3.61 \cdot 10^{-3}$
[1.6, 1.7)	$1.13 \cdot 10^{-3}$	$2.36 \cdot 10^{-3}$
[1.7, 1.8)	$1.39 \cdot 10^{-3}$	$1.54 \cdot 10^{-3}$
[1.8, 1.9)	$1.67 \cdot 10^{-3}$	$9.53 \cdot 10^{-4}$
[1.9, 2.0)	$1.93 \cdot 10^{-3}$	$5.54 \cdot 10^{-4}$

# HYBRID MPC OF INDUCTION OF ESCHERICHIA COLI

- Hybrid MPC problem

- switched linear system
- constraints on input  $T_e$  and  $dT_e/dt$
- penalties on tracking error  $y-y_r$  and input rate  $dT_e/dt$



- Closed-loop results

- MPC controller developed with **Hybrid Toolbox** in MATLAB
- Mixed-Integer Linear Program solver GLPK
- solution time: **32 ms** (worst case=**280 ms**) on 1.2 GHz laptop
- sampling time = **10 min**

