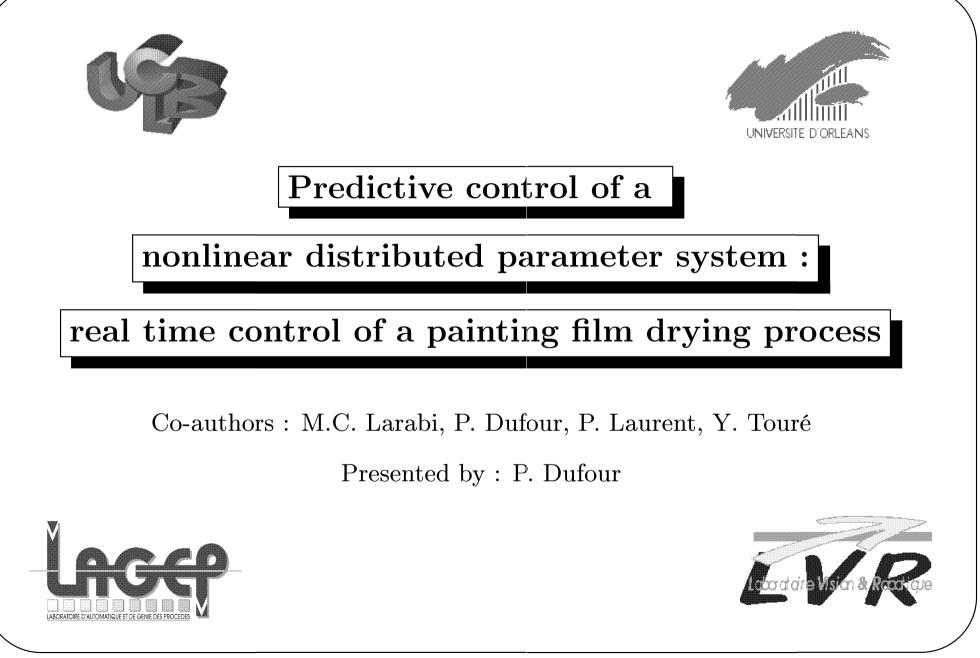
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Context

Process control difficulties are increasing :

 \hookrightarrow necessity of more accurate models :

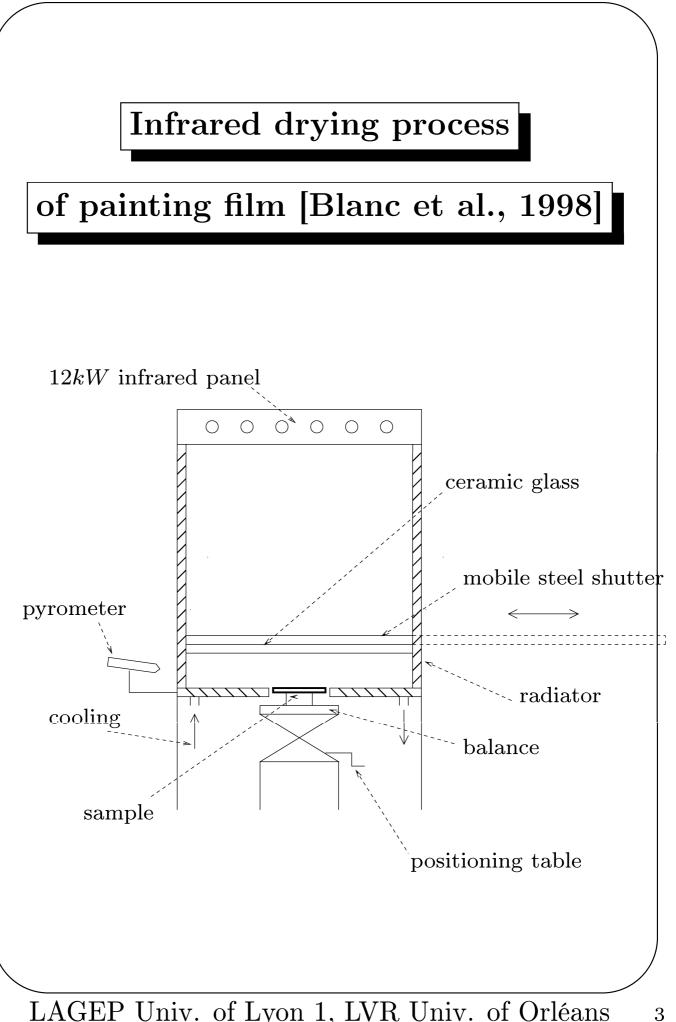
- dynamic aspect
- independant space variables
- nonlinear physical phenomena

 \hookrightarrow nonlinear partial differential equations.

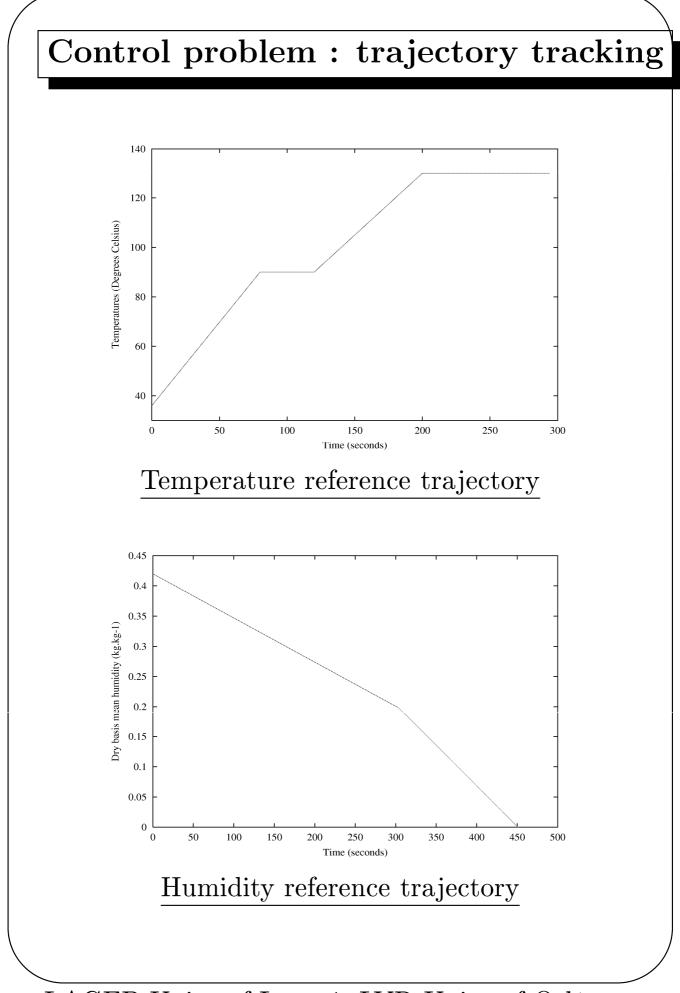
Objectives

Extend the use of the predictive control strategy from systems described by ordinary differential equations to systems described by partial differential equations.

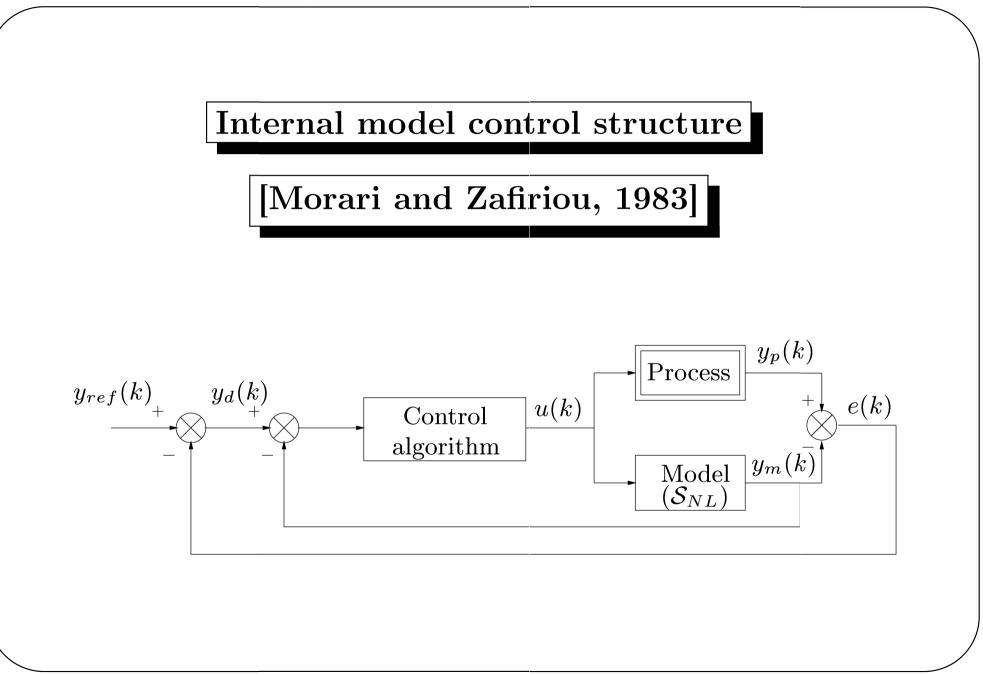
 $\mathbf{2}$



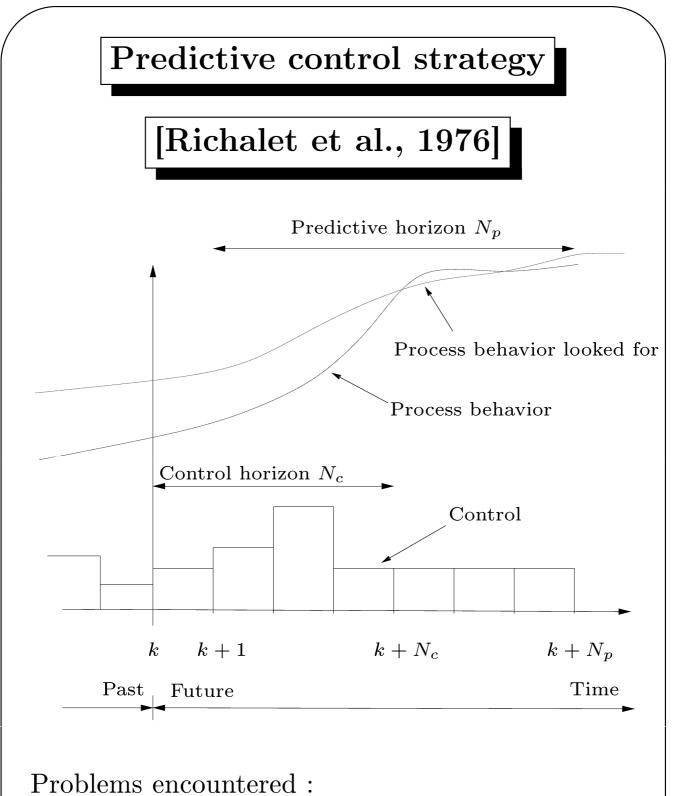
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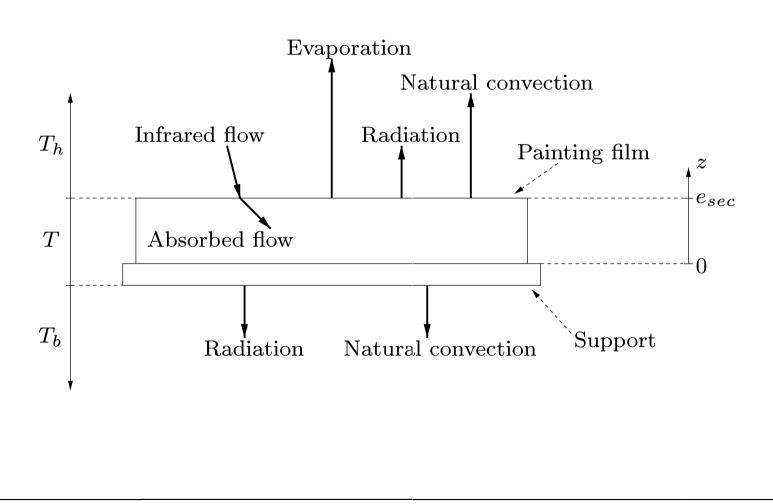


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- real time resolution
- horizons choice
- structural aspects (feasibility, stability)





Energy balance

$$\begin{cases} (\rho_p C_p(\bar{\chi}, T)e_p + \rho_s C_s e_s)\frac{\partial T}{\partial t} = -\sum_{i=1}^5 P_i + P_{abs} \\ T(0) = T_0 \end{cases}$$

with the losses P_i :

$$\begin{cases}
P_1 = h_c(T - T_b), P_2 = \sigma_2(T^4 - T_b^4) \\
P_3 = h_c(T - T_h), P_4 = \sigma_4(T^4 - T_h^4) \\
P_5 = l_v(T)\dot{m}(\bar{\chi}, T)
\end{cases}$$
(2)

and the absorbed infrared flow :

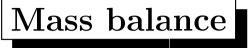
$$P_{abs} = \alpha_{ir}(\bar{\chi})\varphi_{ir}(t)$$

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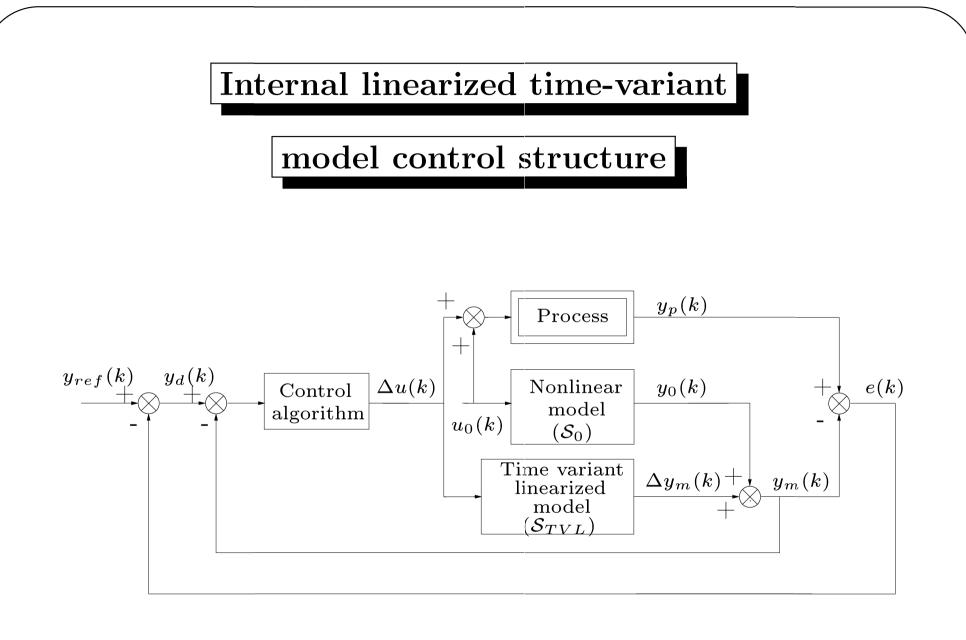
(3)

(1)

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$$\begin{aligned} \frac{\partial \chi}{\partial t} &= \frac{\partial}{\partial z} [D_{eff}(\chi, T) \frac{\partial \chi}{\partial z}] \text{ for } 0 < z < e_{sec}, \ t > 0 \\ \text{with } D_{eff}(\chi, T) &= \frac{D_0 exp^{\left(\frac{-a}{\chi}\right)} exp^{\left(\frac{-Ea}{RT}\right)}}{(1+\phi\chi)^2} \\ \text{with the boundary conditions :} \\ &- D_{eff}(\chi, T) \frac{\partial \chi}{\partial z} = \frac{\dot{m}(\bar{\chi}, T)}{\rho} \text{ for } z = e_{sec}, \ t > 0 \end{aligned}$$
(4)
$$\frac{\partial \chi}{\partial z} = 0 \text{ for } z = 0, \ t > 0 \\ \text{with the initial condition :} \\ &\chi(z, 0) = x_i(z) \text{ for } 0 \le z \le e_{sec} \end{aligned}$$



Real time aspect :

variation model

A model **linearization** about (S_0) characterised by (u_0, x_0, y_0) , with variations checking :

$$\begin{cases} u(k) = u_0(k) + \Delta u(k) \\ x(k) = x_0(k) + \Delta x(k) \\ y_m(k) = y_0(k) + \Delta y_m(k) \end{cases}$$
(5)

leads to :

$$(\mathcal{S}_{LTV}) \begin{cases} \frac{\partial \Delta x}{\partial t} = \frac{\partial F_d}{\partial x|_{(S_0)}} \Delta x \text{ over } \Omega \times]0, +\infty[\\ \frac{\partial F_b}{\partial x|_{(S_0)}} \Delta x + \frac{\partial F_b}{\partial u|_{(S_0)}} \Delta u = 0 \text{ over } \partial \Omega \times]0, +\infty[\\ \Delta y_m = C \Delta x \text{ over } \bar{\Omega} \times]0, +\infty[\\ \Delta x(z, 0) = 0 \text{ with } z \in \bar{\Omega} \end{cases}$$
(6)

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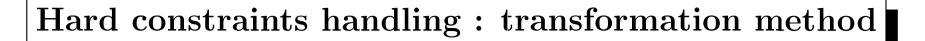


$$\min_{\Delta \tilde{u}} J(\Delta \tilde{u}) = \frac{1}{N_p} \sum_{j=k+1}^{j=k+N_p} g(\Delta u(j-1), \ \Delta y_m(j))$$

$$\Delta \tilde{u} = [\Delta u(k) \dots \Delta u(k+N_c-1)]^T$$

$$c_i(\Delta u(j-1)) \le 0 \qquad (i \in \mathcal{I}, \ j \in \{k+1, \ k+N_c\})$$

$$\left\{ \begin{array}{l} \frac{\partial \Delta x}{\partial t} = \frac{\partial F_d}{\partial x_{|(S_0)}} \text{ over } \Omega \times]0, +\infty[\\ \frac{\partial F_b}{\partial x_{|(S_0)}} + \frac{\partial F_b}{\partial u_{|(S_0)}} = 0 \text{ over } \partial \Omega \times]0, +\infty[\\ \Delta y_m = C\Delta x \text{ over } \bar{\Omega} \times]0, +\infty[\\ \Delta x(z,0) = 0 \text{ with } z \in \bar{\Omega} \end{array} \right.$$
(7)

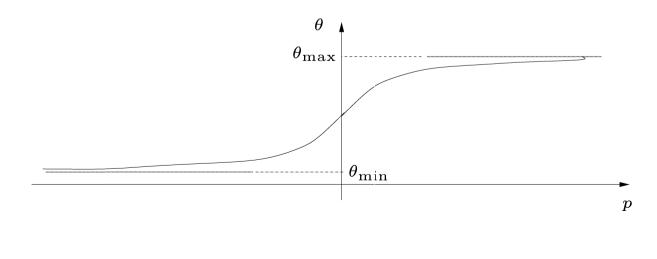


From the **constrainted variable** θ :

$$\theta_{\min} \le \theta \le \theta_{\max}$$
(8)

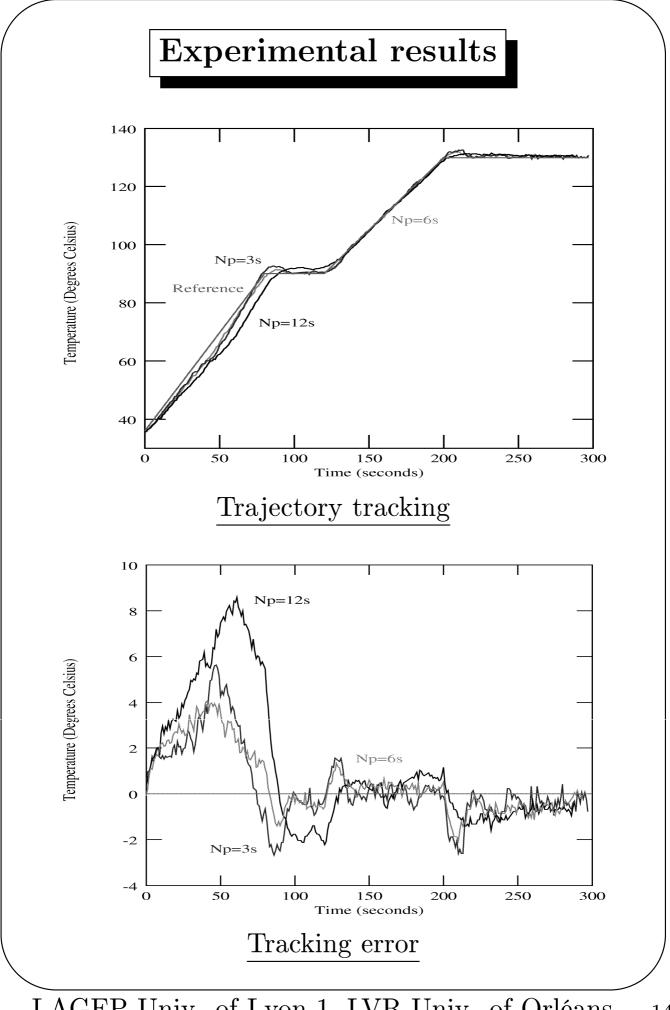
an **unconstrained variable** p is defined such that:

$$\theta = f(p) = \frac{1}{2}(\theta_{\max} + \theta_{\min}) + \frac{1}{2}(\theta_{\max} - \theta_{\min})\tanh(p)$$
(9)

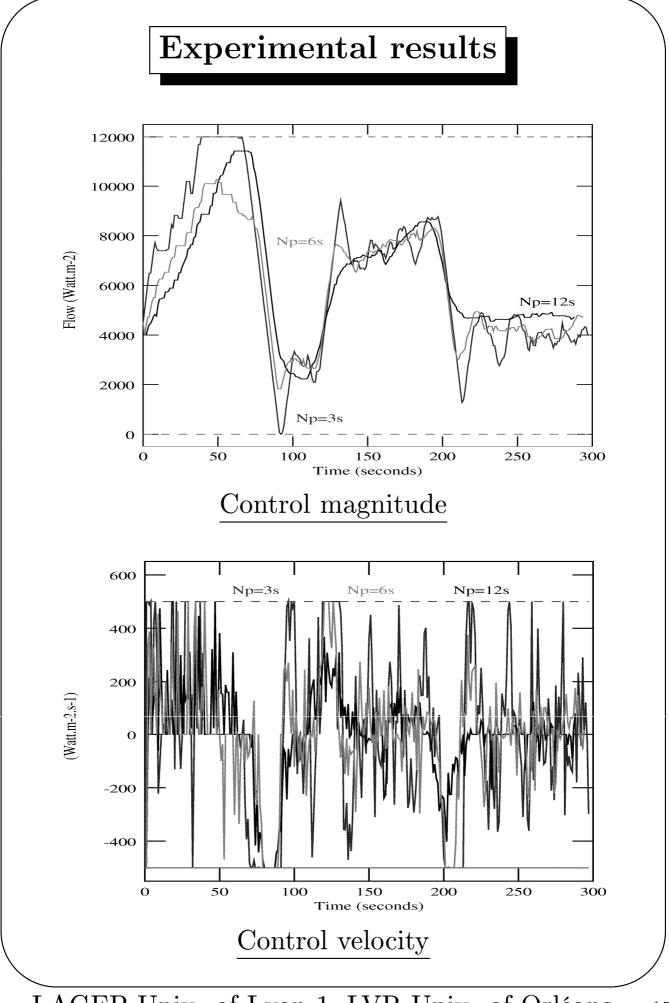


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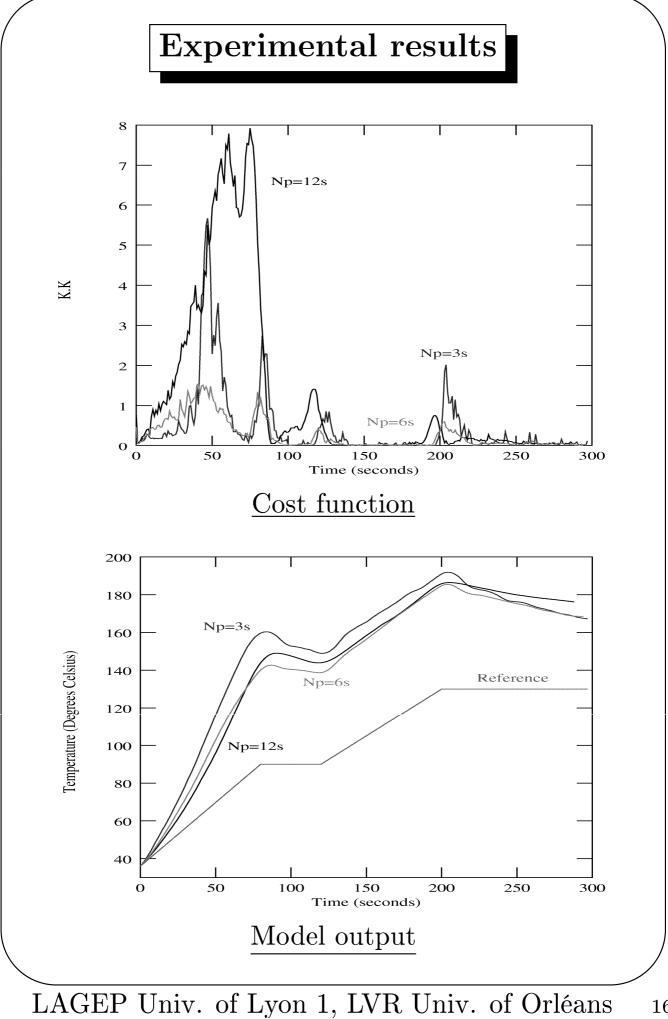


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Conclusions

- Extend the use of the model predictive control strategy to complex systems :
 - \hookrightarrow described by **partial differential** equations
 - \hookrightarrow strongly **nonlinear phenomena**
- Real time control aspect :
 - \hookrightarrow nominal behavior given off line
 - \hookrightarrow on line correction
- Horizons influence
- Behavior interpretation :
 - \hookrightarrow multi disciplinary study.

Prospects

- For a strongly noisy output : use of a receding horizon observer.
- Stability of the closed loop system.

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