



# Title: Model reduction and thermal regulation by Model Predictive Control of a new cylindricity measurement apparatus



**le cnam**



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## 1. Experimental device

## 2. Model reduction

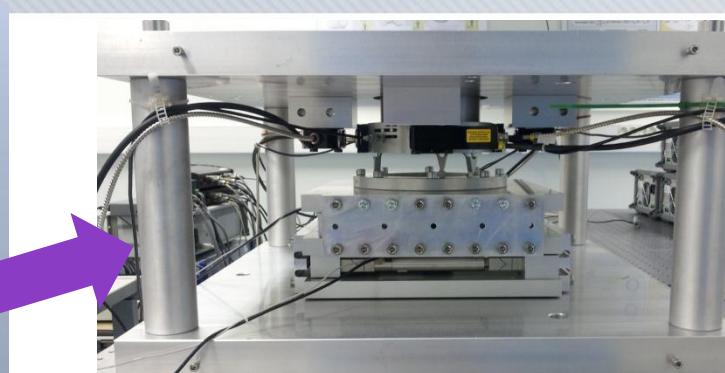
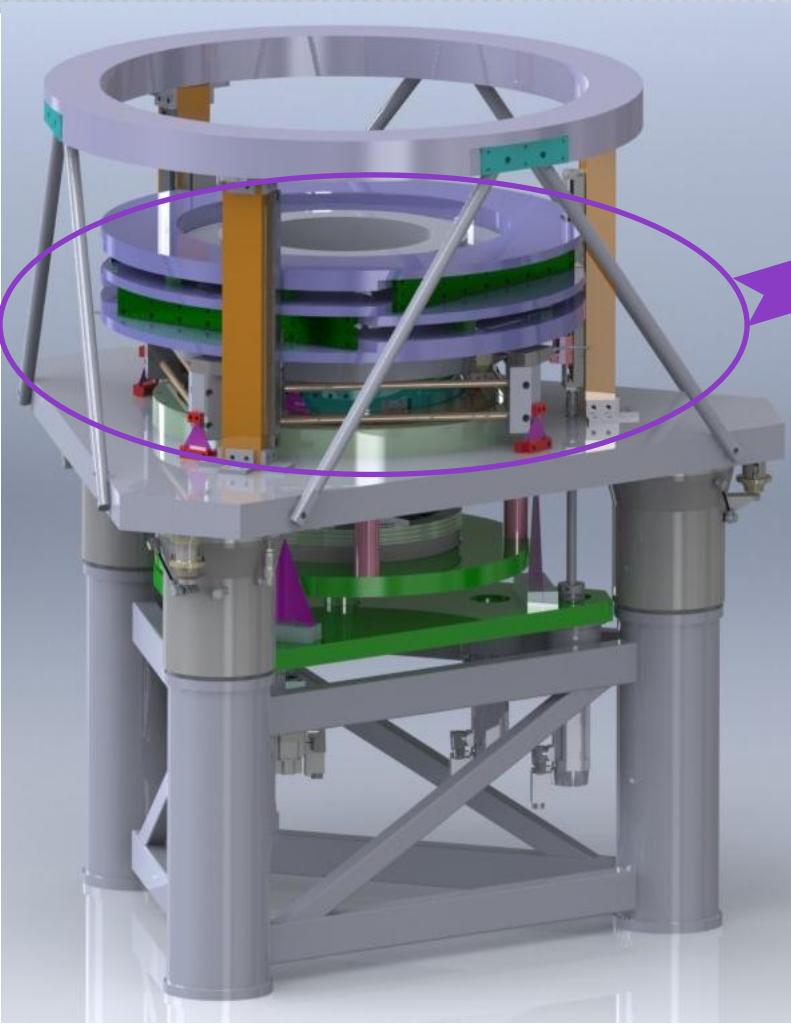
- **Modal Identification Method**
- **Identification of the parameters of the reduced model**

## 3. State feedback control

### Model Predictive Control (MPC)

## 4. Control test cases

## 5. Conclusion and prospects

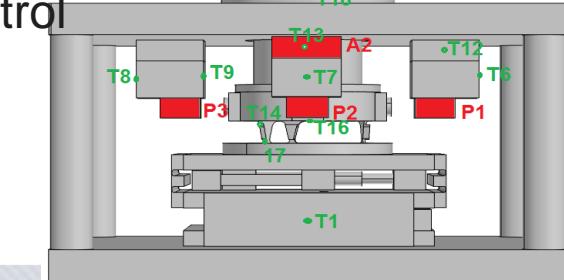
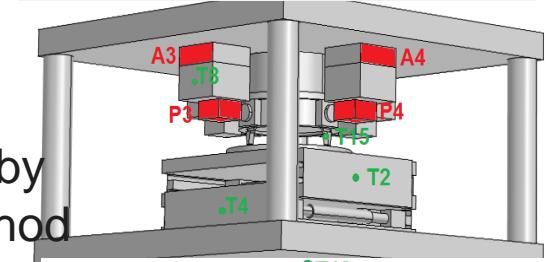
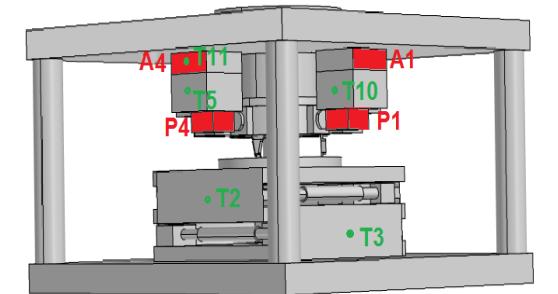


## Issues :

- Heat dissipation
- Thermal dilatation

## Tools:

- Reduced model built by Modal Identification Method
- Model Predictive Control



## Objective :

Real time control to reduce the effects of temperature variation

# Model reduction

## Thermal modeling :

Energy balance:

$$\vec{V} \cdot (k(M) \vec{\nabla} T(M, t)) + \sum_{j=1}^{n_Q} \left[ \frac{P_j(t)}{V_j} \chi_j(M) \right] = \rho(M) C_p(M) \frac{\partial T}{\partial t}(M, t), \\ \forall M \in \Omega$$

Boundary conditions :

$$k(M) \vec{\nabla} T(M, t) \cdot \vec{n} = h(T_a(t) - T(M, t)), \forall M \in \Gamma$$

$$k(M) \vec{\nabla} T(M, t) \cdot \vec{n} = \frac{A_i(t) \xi_i(M)}{S_i}$$

## Resolution of the heat transfer equation

Spatial discretization: - Finite elements  
- Finite volumes  
- Finite differences

State space representation:

$$\begin{cases} \dot{T} = AT(t) + BU(t) \\ Y(t) = CT(t) \end{cases}$$

N ODE

## Issues:

- Memory
- Large computation time
- Unsuitable for real-time control

## Solution

- Find a model reproducing the behaviour of the system with a small number of differential equations (model reduction)



## 1. Definition of a suitable structure of the reduced model

Modal state-space representation

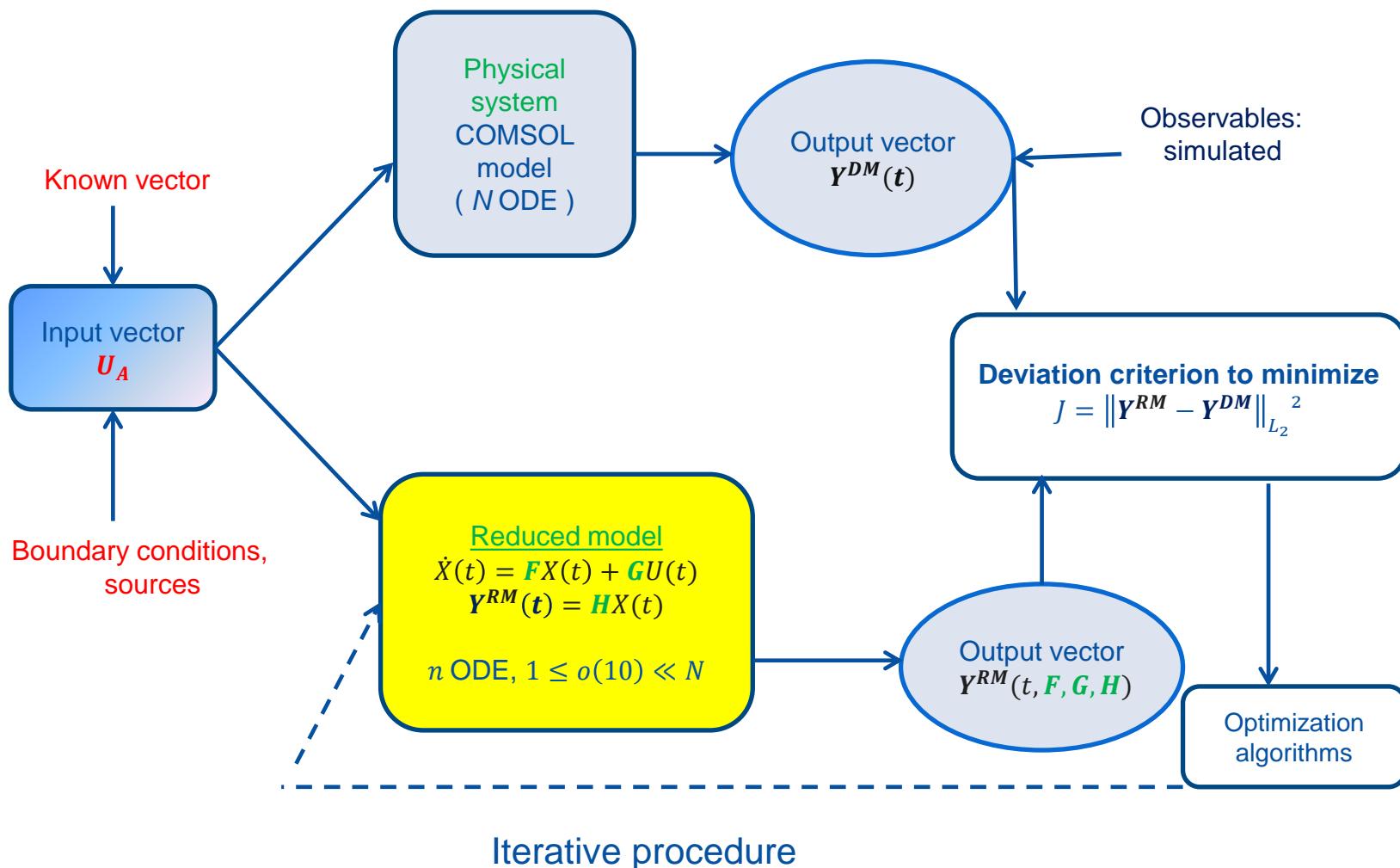
$$\begin{cases} \dot{X}(t) = \mathbf{F}X(t) + \mathbf{G}U(t) \\ \mathbf{Y}(t) = \mathbf{H}X(t) \text{ n ODE, n } \ll N \end{cases}$$

## 2. Generation of numerical output data for a set of known input signals

## 3. Identification of the parameters of the reduced model ( F,G,H ) through optimization algorithms:

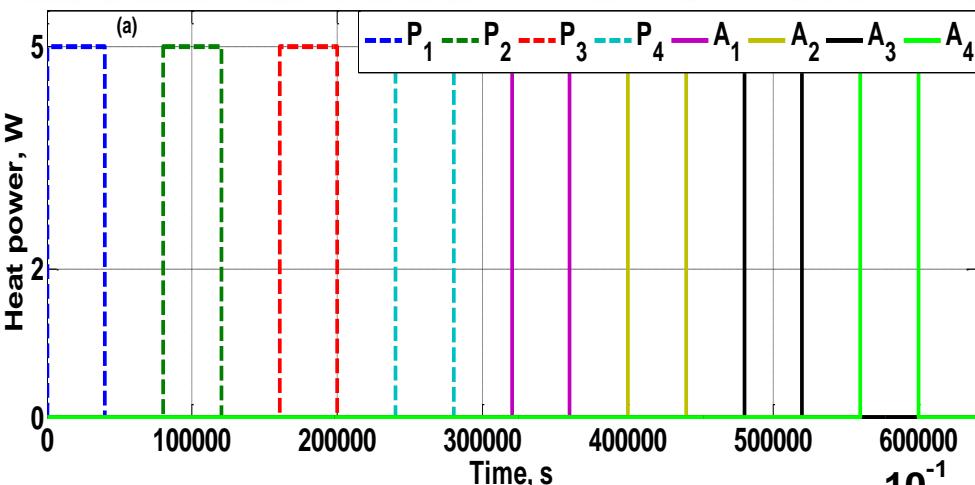
- ❖ Ordinary Linear Least Squares ( $\mathbf{H}$ )
- ❖ Particle Swarm Optimization ( $\mathbf{F}, \mathbf{G}$ )

# Model Identification Method



Model Identification Method scheme

# Identification of the RM



$$U(t) = \begin{bmatrix} A_1(t) \\ \vdots \\ A_4(t) \\ P_1(t) \\ \vdots \\ P_4(t) \end{bmatrix}$$

$$Y(t) = \begin{bmatrix} T_1 \\ \vdots \\ T_{18} \end{bmatrix}$$

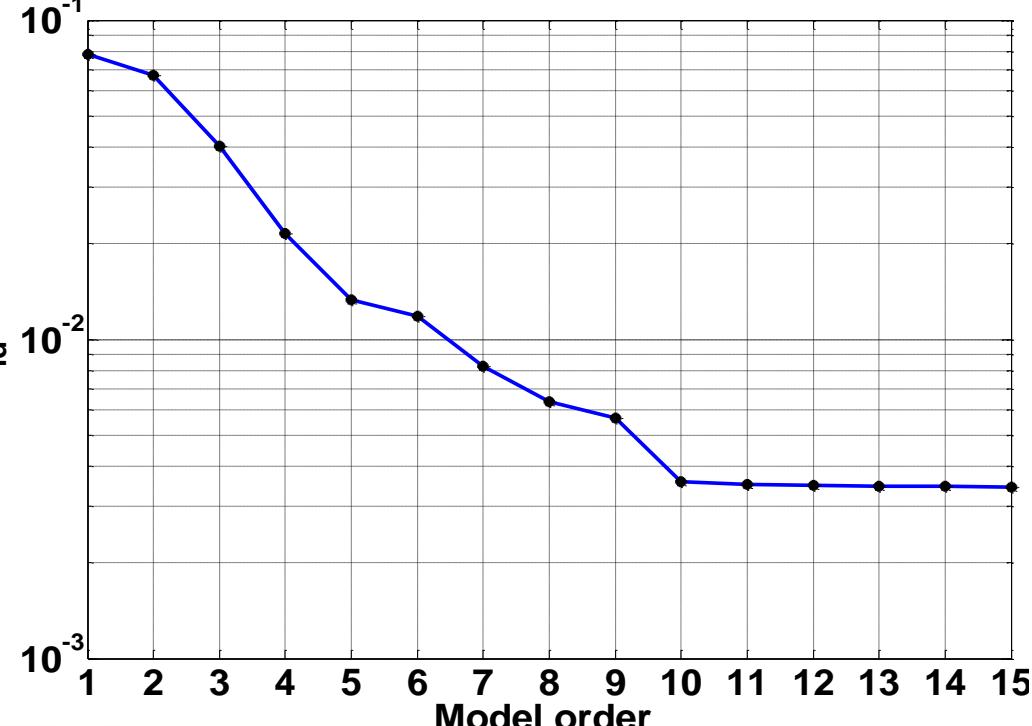
## Quadratic criterion:

$$\sigma_{id}^n = \sqrt{\frac{\sum_{i=1}^q \sum_{j=1}^{N_t} (Yrm_i(t_j) - Y_i^{DM}(t_j))^2}{q \times N_t}}$$

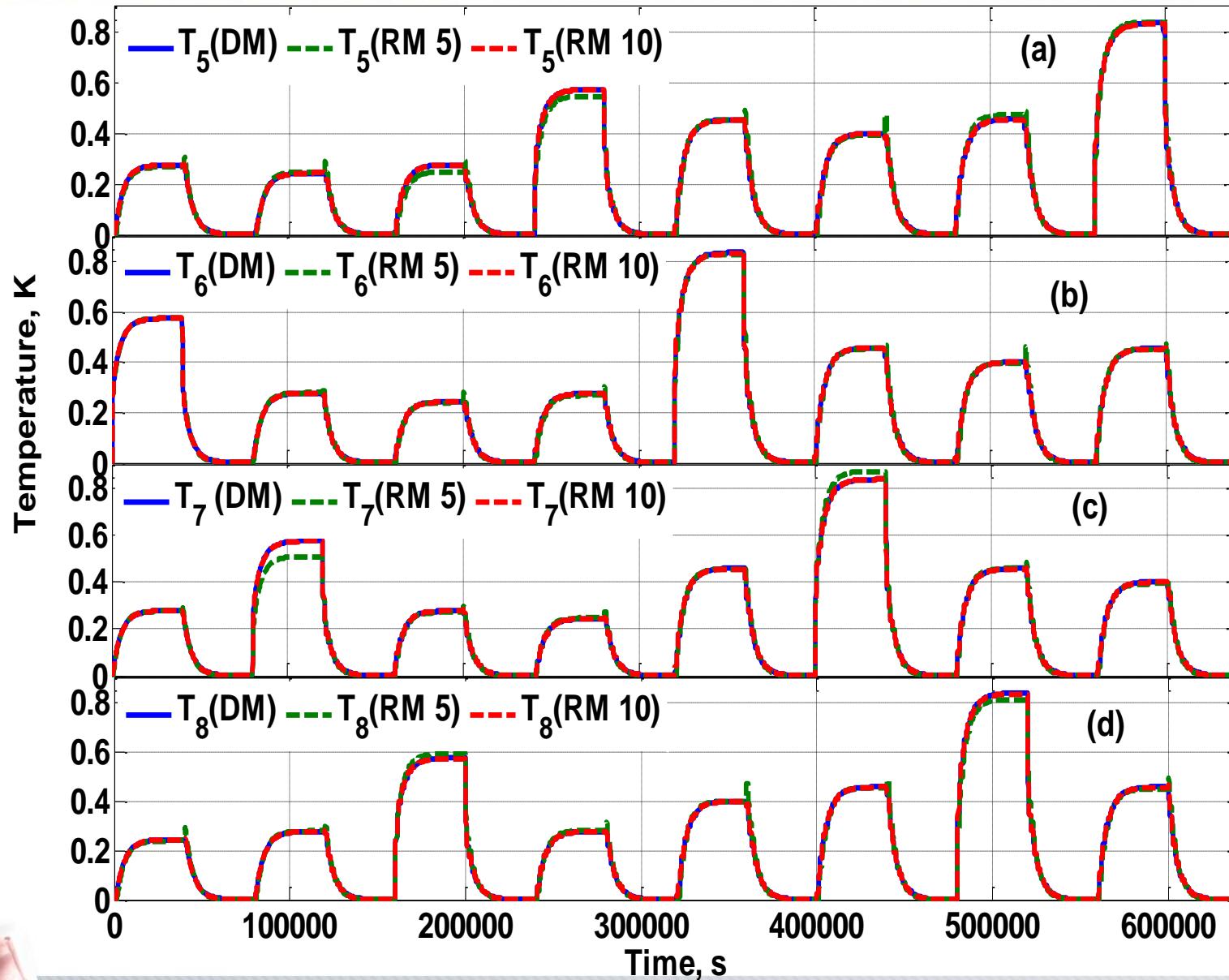
Where:

$q$  is the number of observables

$N_t$  the number of time steps



# Identification of the RM



# State feedback control:

$$\begin{cases} \dot{X}(t) = FX(t) + G_A U_A(t) + G_P U_P(t) \\ Y^{RM}(t) = HX(t) \end{cases}$$

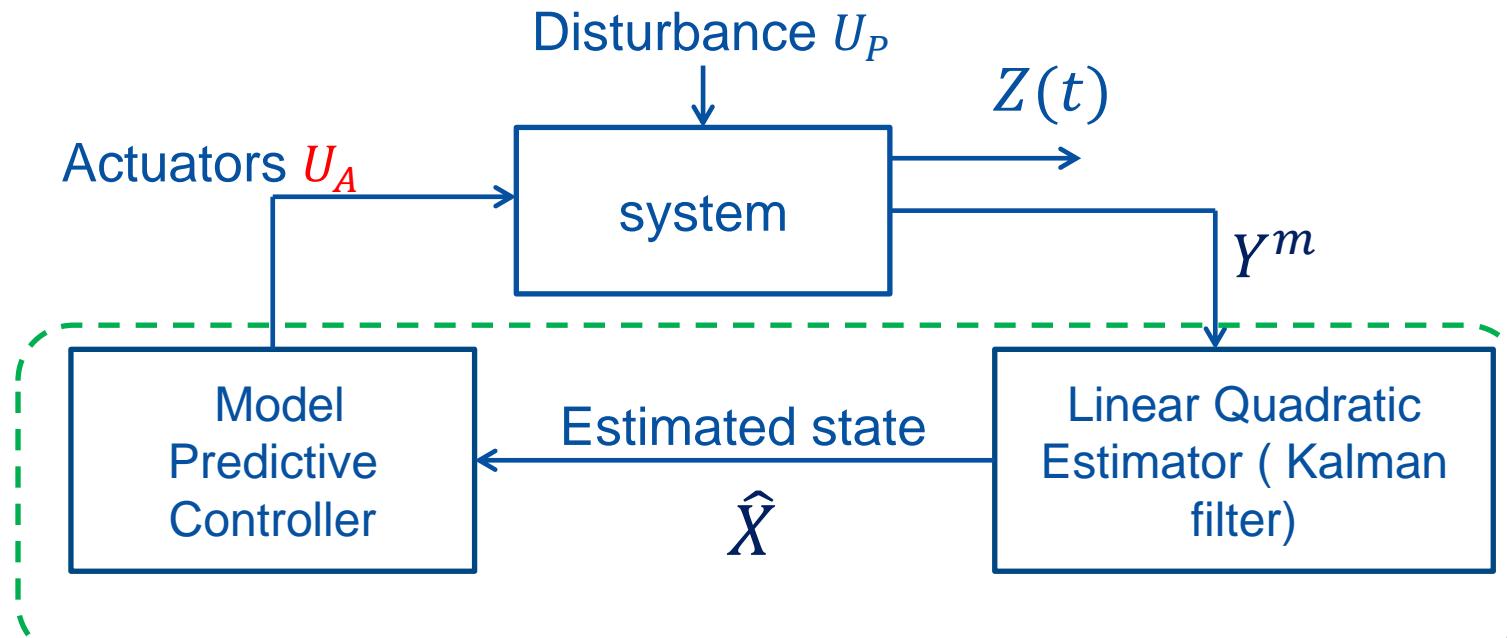
Temperatures to control :

$$Z(t) = [T_5, T_6, T_7, T_8]^T = H_z X(t)$$

Where :

$U_A(t) = [A_1(t), A_2(t), A_3(t), A_4(t)]^T$  = input vector of actuators (surface heaters)

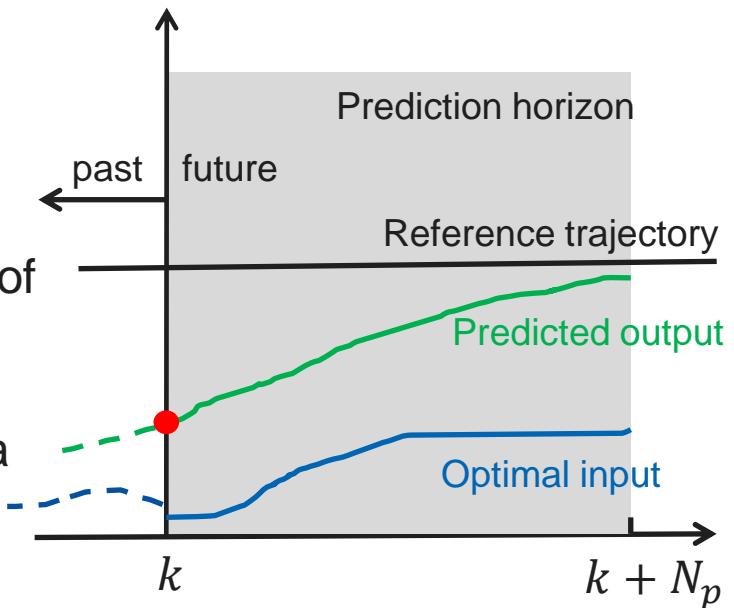
$U_P(t) = [P_1(t), P_2(t), P_3(t), P_4(t)]^T$  = input vector of perturbations  
(laser interferometers)



## Principle :

A model of the system is used to predict plants behavior and choose the best control in the sense of some cost function within constraints.

The future response of the plant is predicted over a Prediction horizon  $N_p$ .



Dynamical system issued from time discretization of the state-space representation:

$$\mathbf{Z}(k) = \boldsymbol{\Psi}X(k) + \boldsymbol{\Gamma}U_A(k-1) + \boldsymbol{\Theta}\mathbf{U}_A(k)$$

- $k$  is the current time index
- $N_p$  is the prediction horizon

$$\mathbf{Z}(k) = \begin{bmatrix} Z(k+1) \\ \vdots \\ Z(k+N_p) \end{bmatrix} \quad \mathbf{U}_A(k) = \begin{bmatrix} \Delta U_A(k) \\ \vdots \\ \Delta U_A(k+N_p-1) \end{bmatrix}$$

The matrices  $\Psi, \Gamma, \Theta$  depend on the matrices F,G,H of the reduced model.

The performance index to minimize :

$$J = \Delta Z^T \Delta Z + \lambda U_A^T U_A$$

The control law issued from the minimization of a quadratic functional is :

$$U_A(k) = (\Theta^T \Theta + \lambda I)^{-1} \Theta^T [Z_{ref}(k) - \Psi X(k) - \Gamma U_A(k-1)]$$

$\lambda$  is a penalty parameter.

$X(k)$  is obtained by using a linear quadratic estimator (Kalman filter)

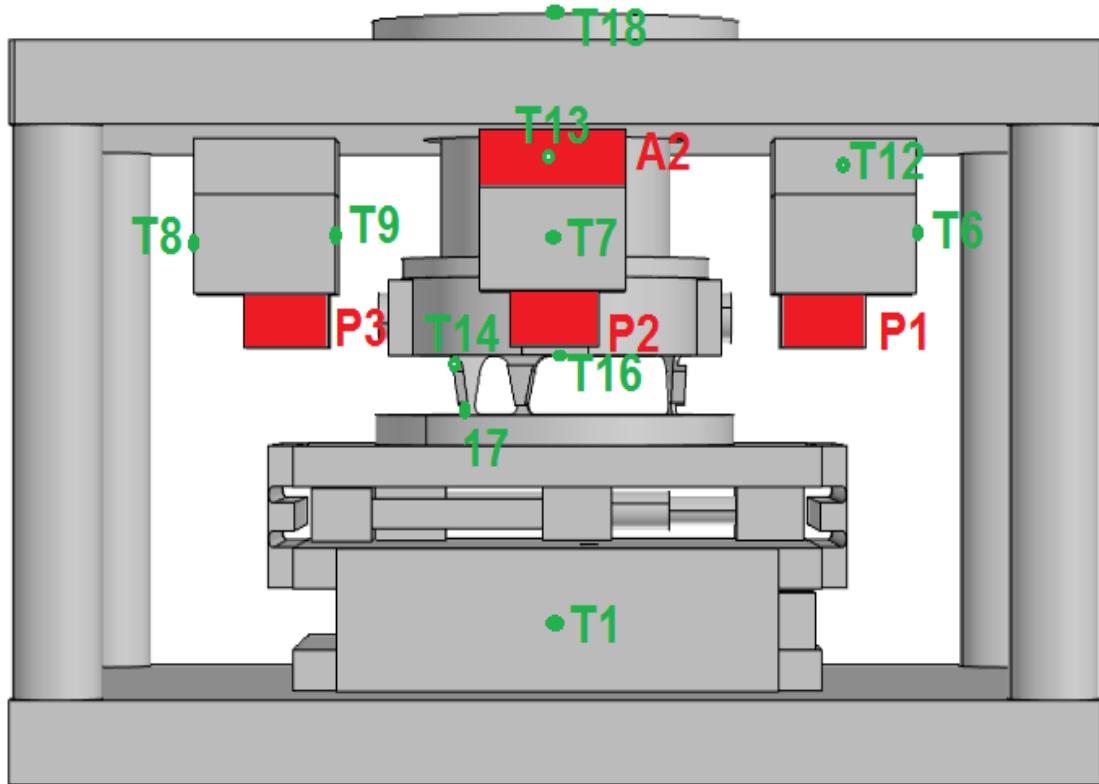


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# Control test case :



## Control parameters :

Temperatures to control:

$$T_5, T_6, T_7, T_8$$

Reduced model:

RM10

Control time step:

$$\Delta t = 1\text{ s}$$

Prediction horizon:

$$N_p = 1$$

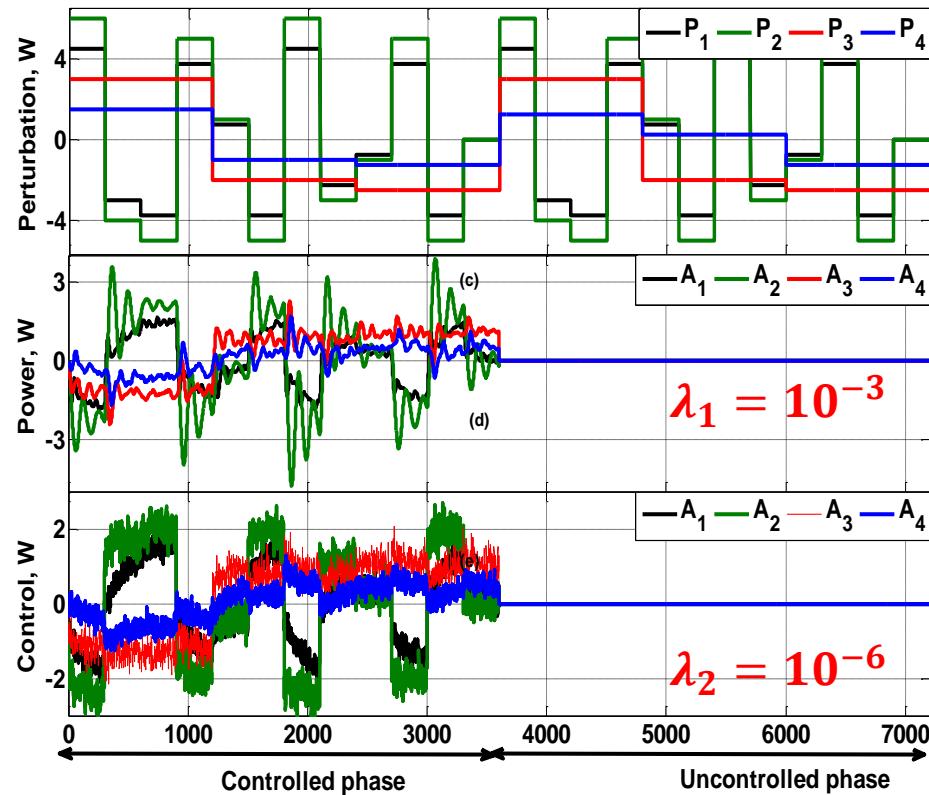
Standard deviation of the measurement noise:

$$\sigma_m = 0.002 \text{ K}$$

The mean quadratic discrepancy between the desired (0K) and the obtained temperatures deviations:

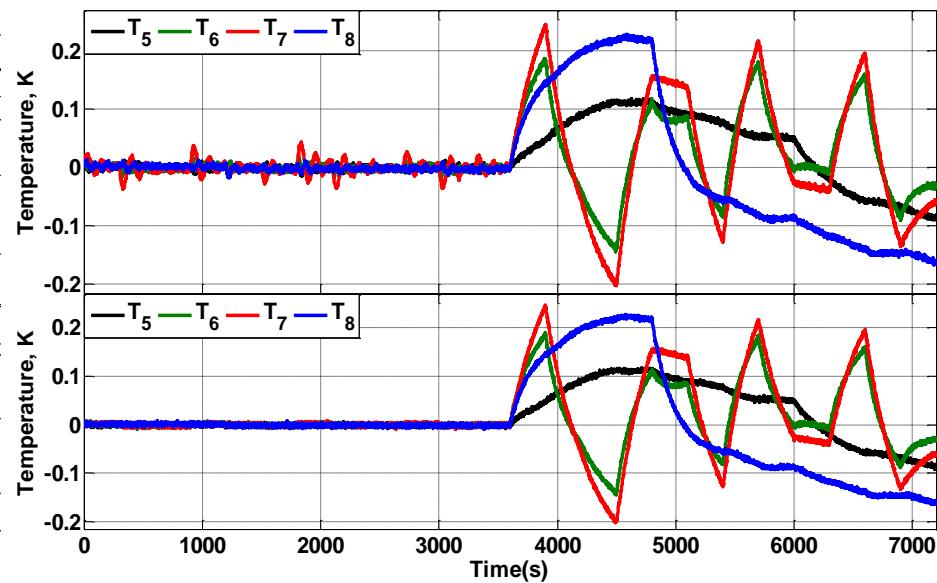
$$\sigma_z = \left( \frac{1}{4 \times N_t} \sum_{j=1}^{N_t} \sum_{i \in \{1,4\}} (Z_i(t_j))^2 \right)^{1/2}$$

# Test case 1



Standard deviation of the perturbation:

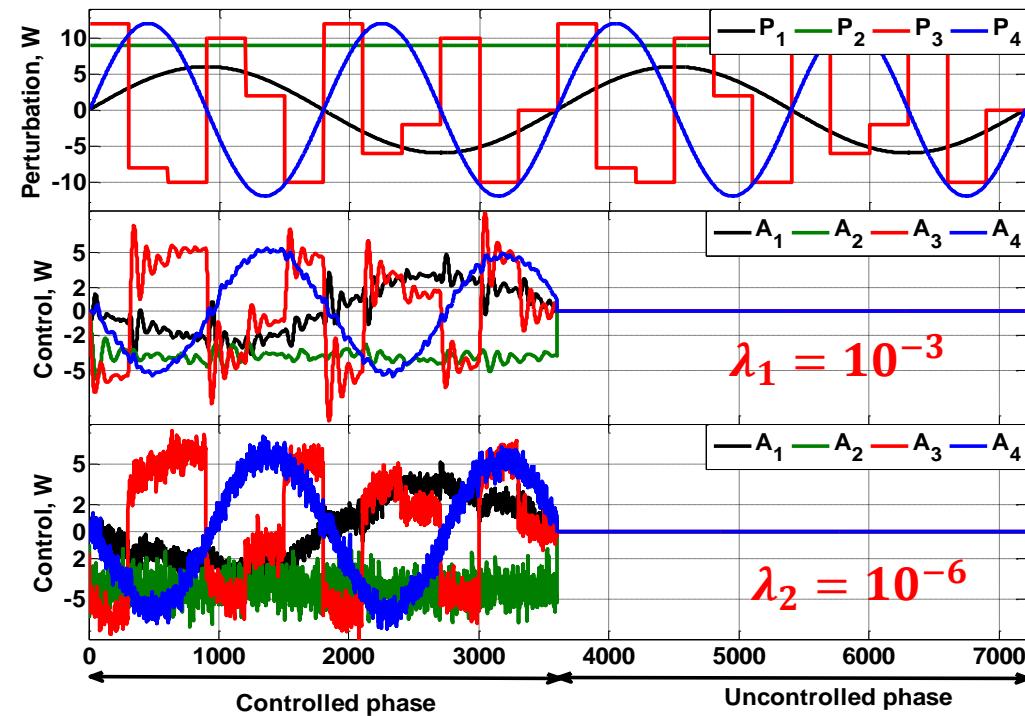
$$\sigma_p = 2.99 \text{ W}$$



	Without control	With control	
$\sigma_z, K$	0.1051	0.0065	0.0024

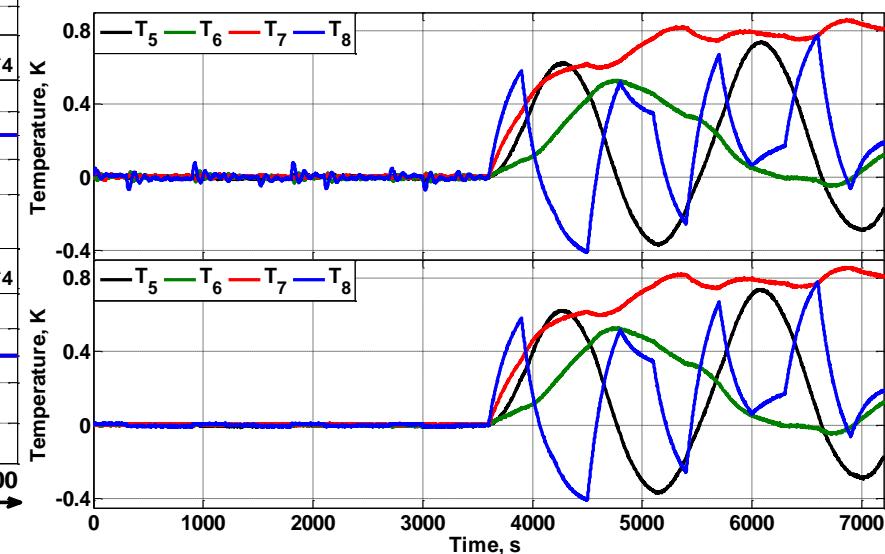


# Test case 2



Standard deviation of the perturbation:

$$\sigma_p = 6.42W$$



	Without control	With control
$\sigma_z, K$	0.4572	0.0120
		0.0041



# Conclusions and prospects

- Numerical generation of input-output data
- A reduced model built with the MIM from numerical generation
- Thermal regulation of temperature in 4 points of the structure

- Study the effects of the MPC parameters
- Identify a reduced model from experimental data
- Increase the number of controlled points



*Thank you for your  
attention*

## State estimation:

$$\dot{\hat{X}}(t) = F\hat{X}(t) + G_A U_A(t) + K_f(Y^{RM}(t) - H\hat{X})$$

The correction is done through the Kalman gain given by :

$$K_f = \frac{1}{\alpha^2} S H^T$$

Where  $S$  ( $\in \mathbb{R}^{n \times n}$ ) is the solution of Riccati equation:

$$S F^T + F S - \frac{1}{\alpha^2} S H^T H S + G_P {G_P}^T = 0$$

$\alpha = \frac{\sigma_m}{\sigma_p}$  is the ratio between the standard deviations of measurements and heat source disturbances