31/05/2023

GDR MASCOT-NUM

Workshop on calibration of numerical code

Global vs Goal-Oriented model updating techniques in deterministic setting – Application to urban issues

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Introduction – Why it is important to study cities ?

Global rise of urbanization

Percentage of world population in cities

Today
55%

2050
68%
expected

The Guardian

Water scarcity

Biodiversity loss

Mairie de Paris

Urban Heat Island

Urban issues

CNN

Poor air quality

Noise pollution

...

Waste-disposal problems

High energy consumption

⇨ Need of advanced city planning for more sustainable cities

The City components

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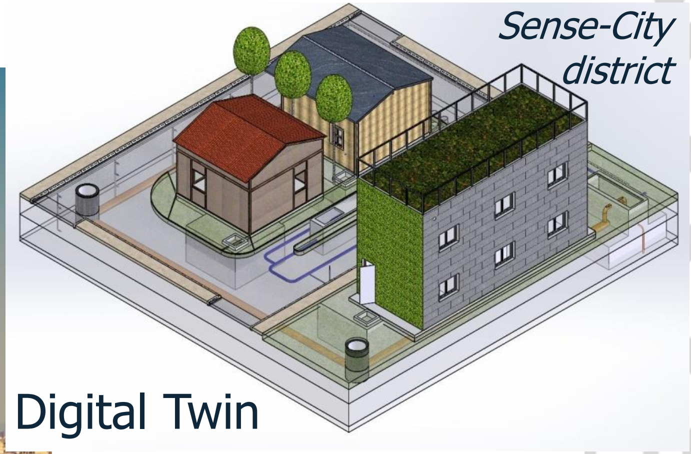
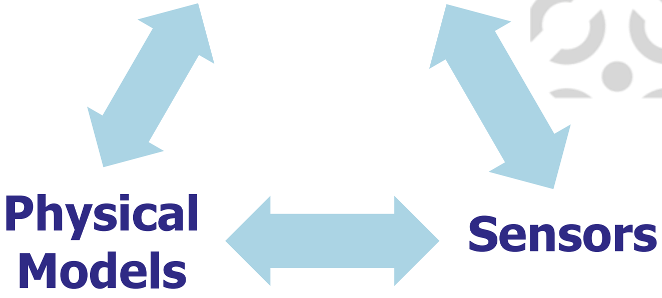
City Digital Twin & Numerical methods

<u>Cross-cutting problematics</u>

- *Sensor placement*
- *Localization of anomalies*
- *Cartography and Prediction*
- *Choice of urban planning and optimal control*



Development of **numerical methods** dedicated to city applications



Focus on « Goal-oriented » deterministic approaches

Quantity of Interest (QoI)

GOAL-ORIENTED

- Discretization error *[Ladevèze & Waeytens 09], [Waeytens et al 12]*
- Model updating *[Chamoin et al 14], [Djatouti et al 20a], [Djatouti et al 20b]*
- Sensor placement *[Waeytens,…, Chatellier 17], [Waeytens & Sadr 18]*
- Urban planning *[Hamada et al, in preparation]*

<u>Topic of the presentation :</u>

- **Global model updating techniques – focus on Constitutive Relation Error approach**
- **Goal-oriented inverse method** for the **prediction of quantities of interest**

Outline of the presentation

1) Introduction

2) Global model updating techniques
applied to *Structural Health Monitoring*

3) Goal-oriented model updating
applied to *Thermal building application*

4) Conclusions & Perspectives

Global model updating techniques

Inverse problems for urban diagnosis

Remark:
Abnormal state can be represented via physical model parameter

Strategy:
Solve an **inverse problem** based on optimal control theory *[Lions 1971]*
where the control parameter U is a physical model parameter

APPLICATIONS

Structural Health Monitoring

Civil Engineering structure with post-tensioned concrete beams

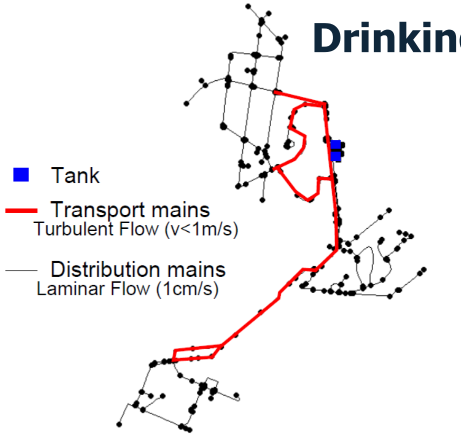
Structural damages → Young modulus

Building thermal performance

Building before renovation operations at Noisiel (77)

Insufficient wall insulation → Thermal resistance

Drinking water networks



Drinking water network in Ile de France

Leaks/irregular water consumptions → Water flow Boundary Conditions

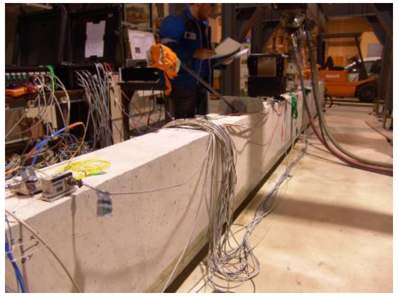
Water quality → Reaction coefficients in water pipes

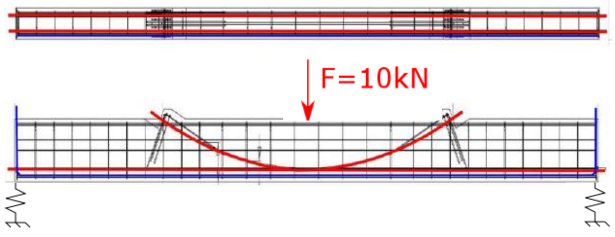
Illustration of global model updating techniques on Structural Health Monitoring

[Waeytens et al 16]

Objective: Localize and quantify structural damages

Application to a
8m post-tensioned concrete beam





Large number of measurements

Strain measured from optic fiber

Modelling

Simple 3D linear elastic model (PDE)

$$\int_\Omega Tr[\epsilon(\mathbf{u})\mathcal{K}(E)\epsilon(\mathbf{u}^*)]d\Omega + \int_{\partial\Omega_i} k u_y u_y^* \partial\Omega - \int_{\partial\Omega_f} F_d u_y^* \partial\Omega = 0$$

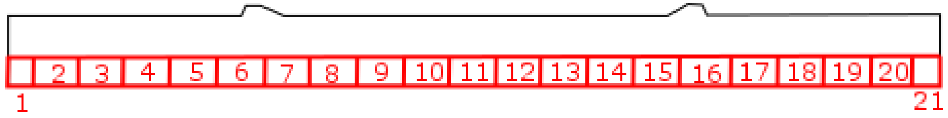
$$\forall \mathbf{u}^* \in \mathcal{U}_0 = \{\mathbf{u}^* \in H_1(\Omega)\}$$

Finite Element discretization

$$\mathbb{K}(\mathbf{E})\mathbf{U} = \mathbf{F}$$

Solve inverse problems

Determine the Young modulus E in the potential damaged sub-domains



Comparison of global model updating techniques:

Classical Tikhonov-based technique

Constitutive Relation Error technique

Bayesian Technique

[Rosic et al 13]

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Outline of classical data misifit functional with Tikhonov regularization

Find **E** minimizing the functional:

$$J_T(\mathbf{E}) = \frac{1}{2}(\mathbb{B}\mathbf{U} - \epsilon^{\mathbf{mes}})^T(\mathbb{B}\mathbf{U} - \epsilon^{\mathbf{mes}}) + \boxed{\frac{\alpha_T}{2} s_T (\mathbf{E} - \mathbf{E}_{\mathbf{ud}})^T(\mathbf{E} - \mathbf{E}_{\mathbf{ud}})}$$

1) Consider Young Modulus **E** from the previous iteration
2) Determine U solving the direct problem: $\mathbb{K}(\mathbf{E})\mathbf{U} = \mathbf{F}$
3) Determine $\mathbf{\Psi}$ solving the adjoint problem:

$$\mathbb{K}\mathbf{\Psi} = \mathbb{B}^T(\mathbb{B}\mathbf{U} - \epsilon^{\mathbf{mes}})$$

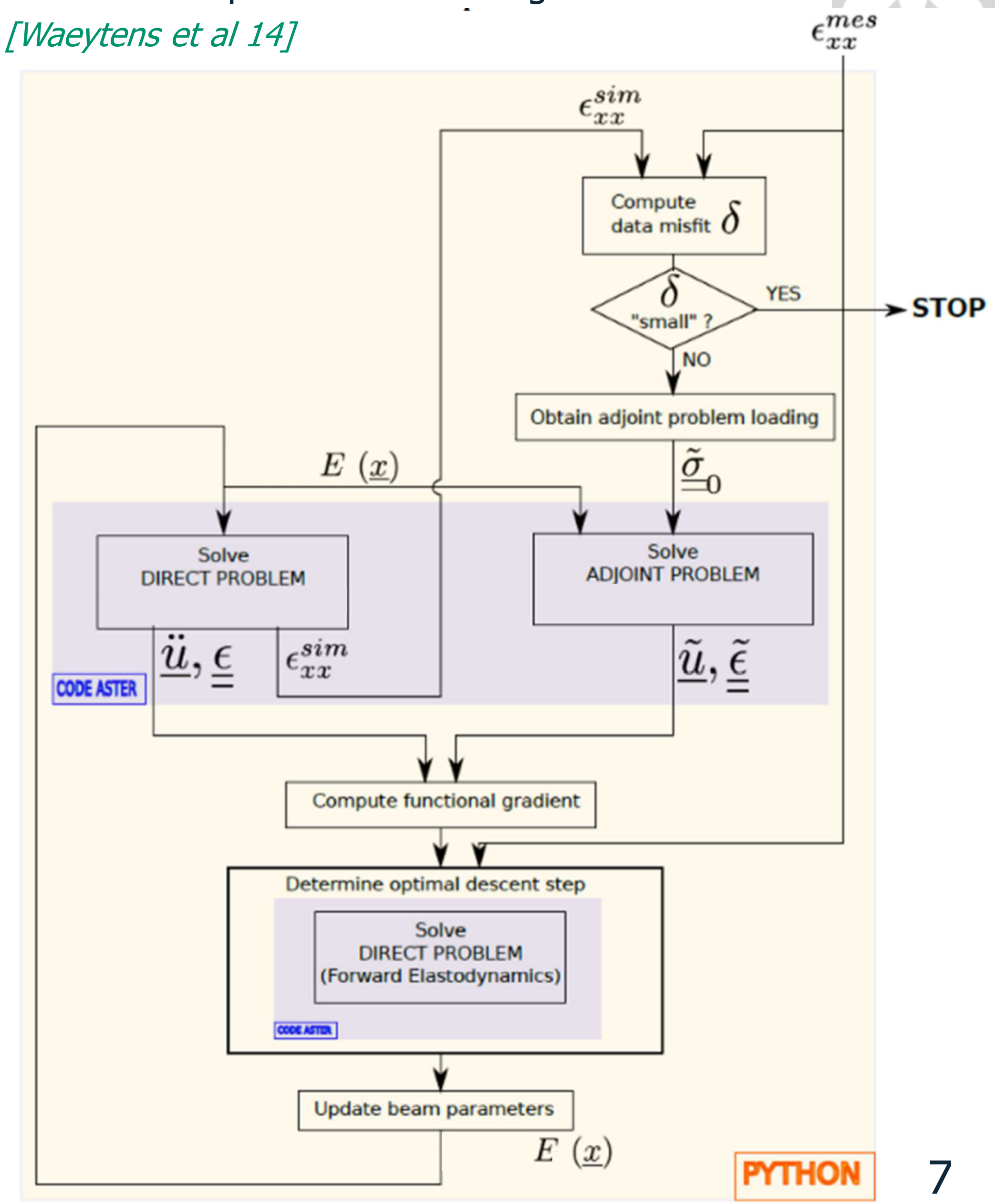
4) Evaluate the gradient of the functional according to **E**

$$\nabla \mathbf{J}_T = \begin{Bmatrix} \frac{\partial J}{\partial E_1} = -\mathbf{\Psi}^T \frac{\partial \mathbb{K}}{\partial E_1}\mathbf{U} + \alpha_T s_T (E_1 - E_{ud}) \\ \vdots \\ \frac{\partial J}{\partial E_{nE}} = -\mathbf{\Psi}^T \frac{\partial \mathbb{K}}{\partial E_{nE}}\mathbf{U} + \alpha_T s_T (E_{nE} - E_{ud}) \end{Bmatrix}$$

5) Update Young Modulus **E** using gradient descent: $\mathbf{E}_{\mathbf{new}} = \mathbf{E}_{\mathbf{old}} - \beta \nabla \mathbf{J}_T$.

Numerical implementation using standard codes

[Waeytens et al 14]



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Global model updating *via* modified Constitutive Relation Error

[Chouaki, Ladevèze, Proslier 1996]

- Main idea: Separate mechanical equations into three categories:
  Kinematic / Static / Constitutive Relation

- Seek (**U**,**V**,**E**) such that it minimizes the modified Constitutive Relation Error (mCRE) functional :

$$J_{CRE}(\mathbf{E}) = \frac{\alpha_{CRE}}{2} s_{CRE} \underbrace{(\mathbb{B}\mathbf{U} - \epsilon^{\mathbf{mes}})^T(\mathbb{B}\mathbf{U} - \epsilon^{\mathbf{mes}})}_{\text{Classical data misfit}} + \underbrace{\frac{1}{2}(\mathbf{U}-\mathbf{V})^T \mathbb{K}(\mathbf{E})(\mathbf{U}-\mathbf{V})}_{\text{Regularization term using Constitutive Relation Error}}$$

where :

The kinematically admissible displacement field **U** satisfies kinematic boundary conditions

The statically admissible displacement field **V** statisfies equilibrium equations in finite element sense:

$$\mathbb{K}(\mathbf{E})\mathbf{V} = \mathbf{F}$$

- Rewriting of the **constrained minimization problem** using a Lagrangian

Summarize of damage detection method
using modified Constitutive Relation Error (CRE) regularization

Find **E** minimizing the functional:

$$J_{CRE}(\mathbf{E}) = \frac{\alpha_{CRE}}{2} s_{CRE} (\mathbb{B}\mathbf{U} - \epsilon^{\mathbf{mes}})^T (\mathbb{B}\mathbf{U} - \epsilon^{\mathbf{mes}}) + \boxed{\frac{1}{2}(\mathbf{U}-\mathbf{V})^T \mathbb{K}(\mathbf{E})(\mathbf{U}-\mathbf{V})}$$

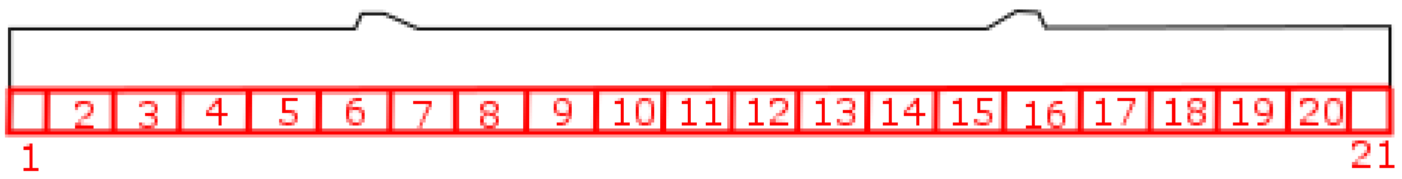
1) Consider Young Modulus **E** from the previous iteration
2) Determine U solving: $(\mathbb{K} + \alpha_{CRE} s_{CRE} \mathbb{B}^T \mathbb{B})\mathbf{U} = \mathbf{F} + \alpha_{CRE} s_{CRE} \mathbb{B}^T \epsilon^{\mathbf{mes}}$
3) Determine V solving: $\mathbb{K}\mathbf{V} = \mathbf{F}$
4) Evaluate CRE associated with each E_i : $\varepsilon^i_{CRE} = \frac{1}{2}(\mathbf{U}_\mathrm{i} - \mathbf{V}_\mathrm{i})^T \mathbb{K}_i(E_i)(\mathbf{U}_\mathrm{i} - \mathbf{V}_\mathrm{i})$
5) Only updates E_i with the highest CRE.

Remark 1: For a given Young modulus **E**, if the field **U** and field **V** are equals, then the data misfit vanishes.

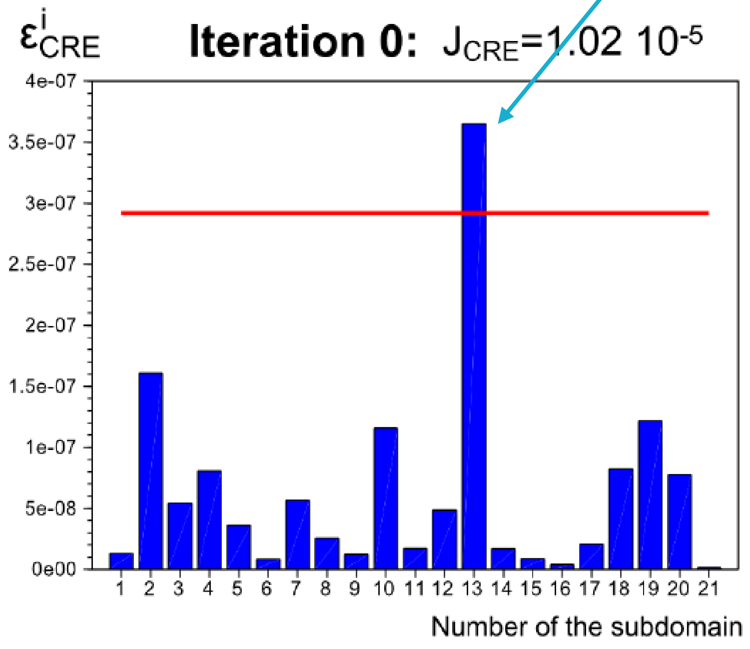
Remark 2: Determination of the weight parameter α_{CRE} using Morozov principle. *[Morozov 1966]*
→ *Data misfit must not be less than the measurement error*

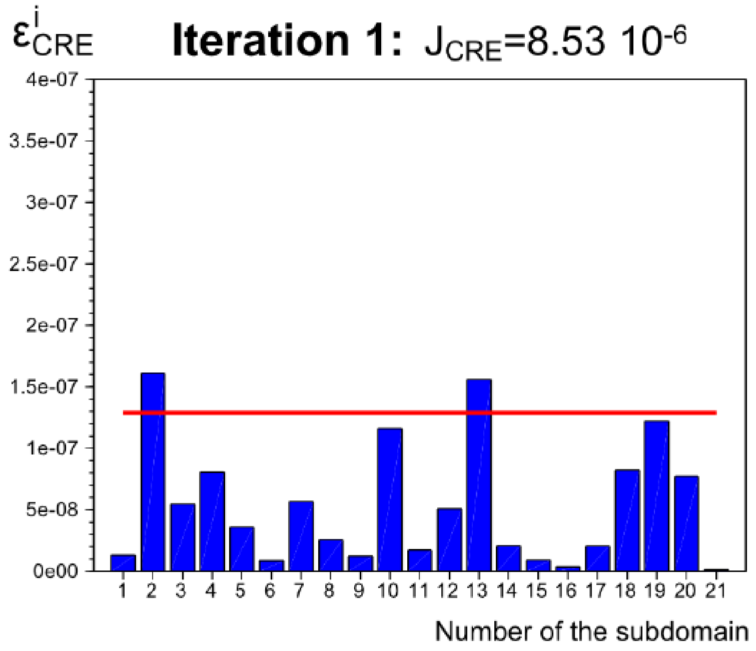
Results obtained with Modified Constitutive Relation Error (mCRE) technique

Determination of Young Modulus in 21 potential damaged sub-domains



Highest mCRE in sub-domain #13





Updating of Young Modulus
in subdomain 13

Updating of Young Modulus
in subdomains 2 & 13

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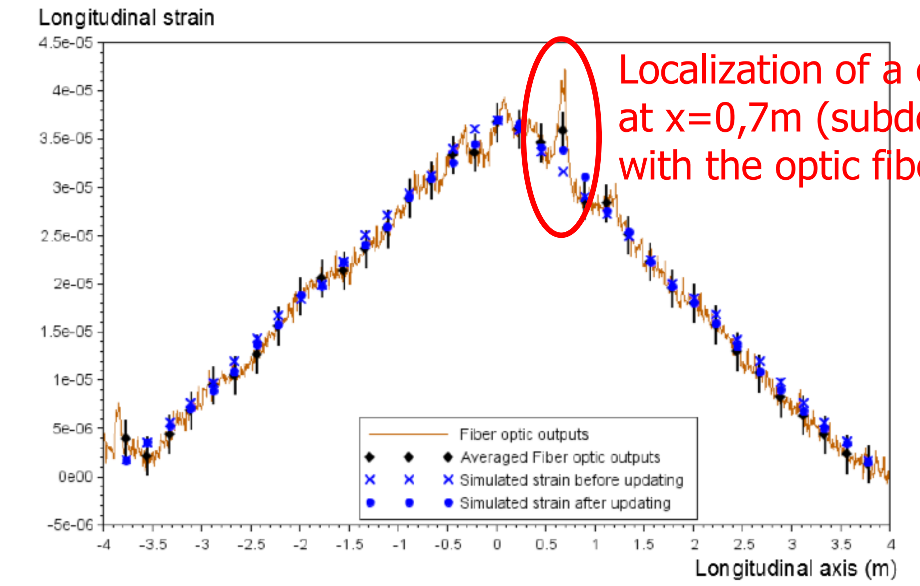
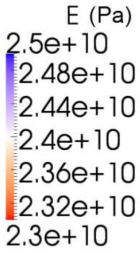
Comparison of the results: Tikhonov – mCRE – Bayesian model updating

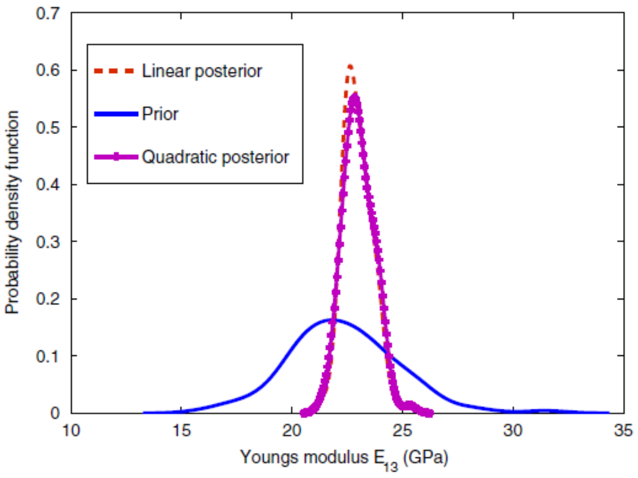
[Waeytens et al 16]

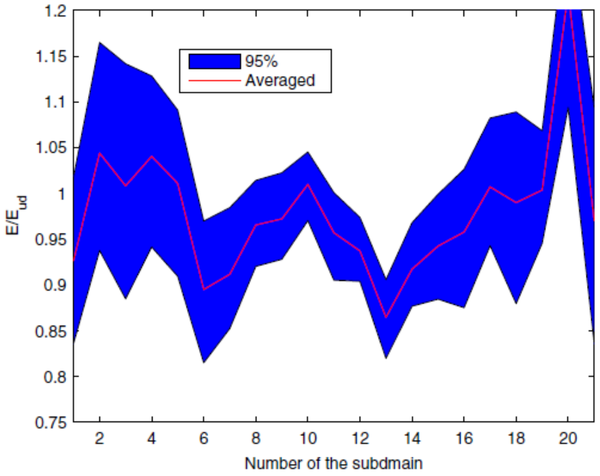


Strain sensor outputs with optic fiber & simulated strain

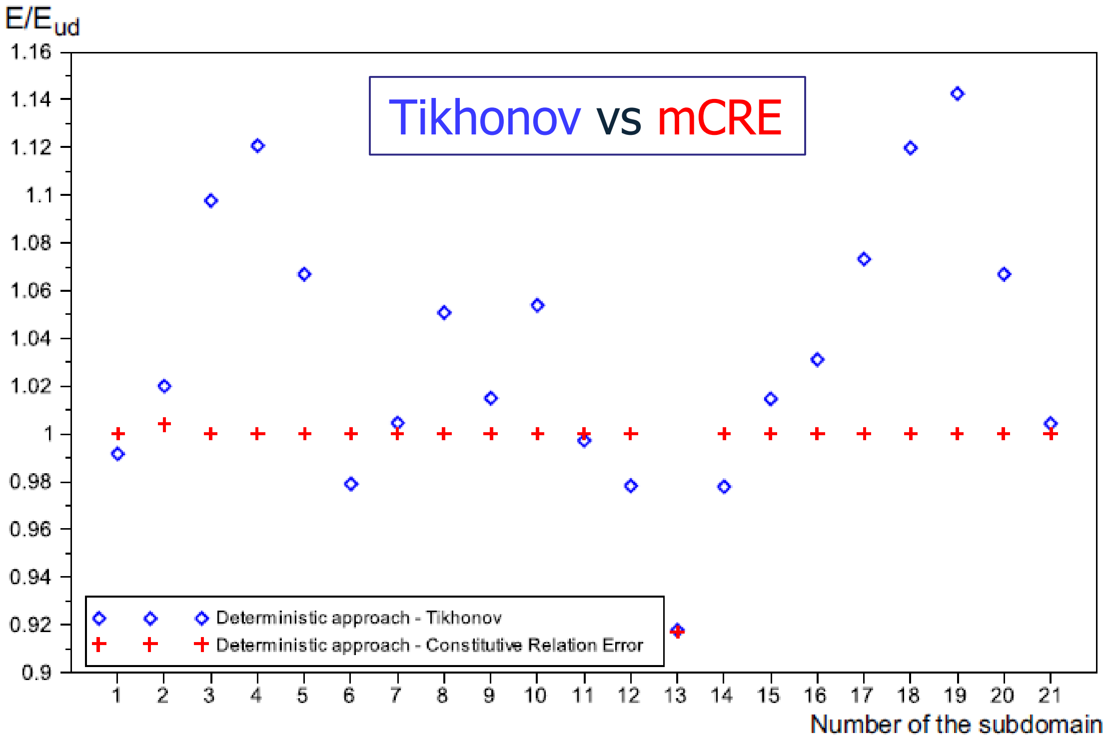
Localization & **quantification**
of the damage (red area)
8% Young modulus decrease
-
Inverse method with mCRE







Bayesian model updating results



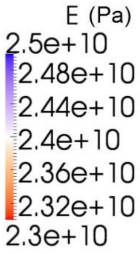
Comparison of the results: Tikhonov – mCRE – Bayesian model updating

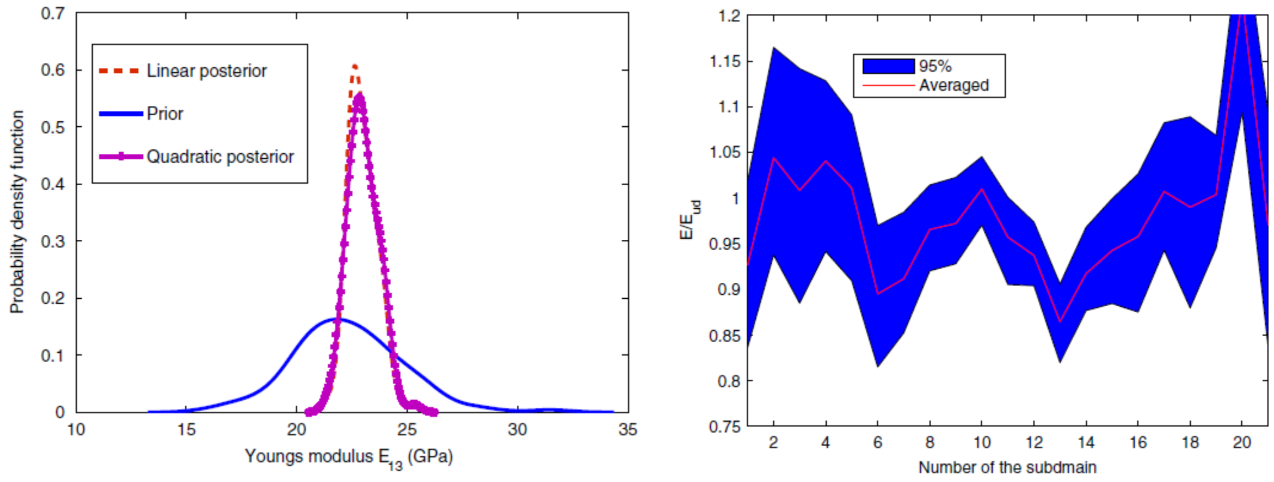
[Waeytens et al 16]

Conclusions:

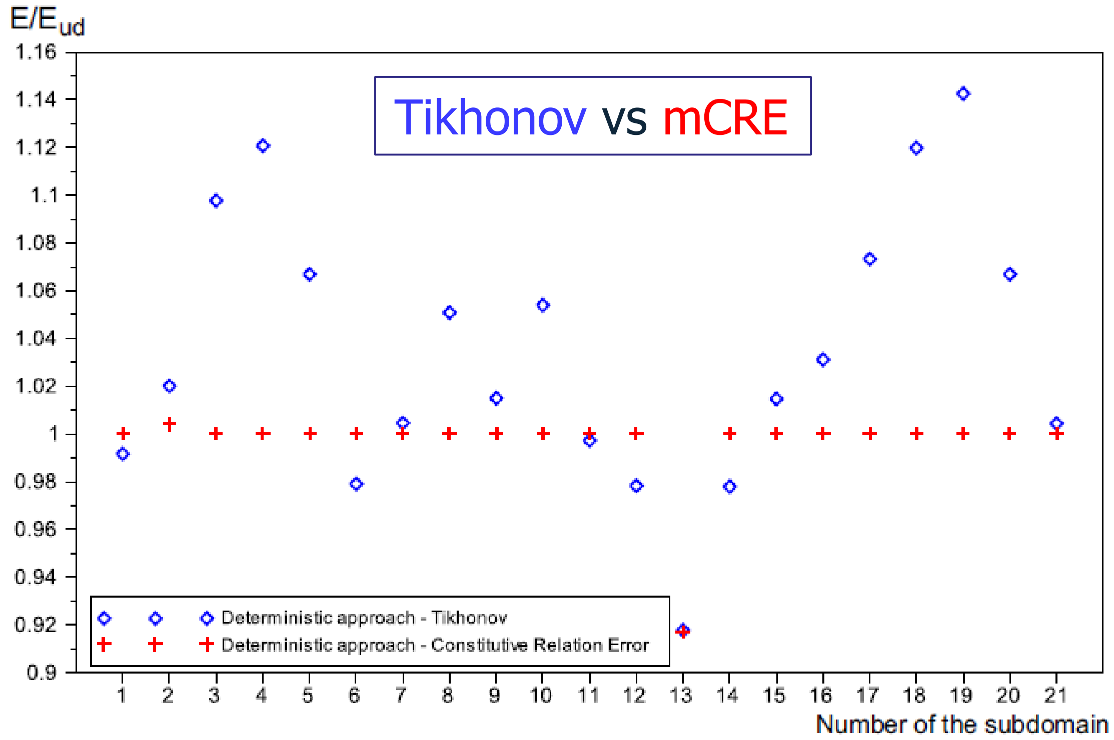
- All the methods detect a damage in subdomain #13
- Localized update with mCRE (only subdomain #13) whereas the other techniques identify all Young modulus
- Similars results for Tikhonov and Bayesian techniques.

Localization & **quantification** of the damage (red area)
8% Young modulus decrease
-
Inverse method with mCRE





Bayesian model updating results



« Goal-oriented » model updating for accurate prediction of quantities of interest

Thermal building application

Context and Motivations

Building surface temperature obtained with an infrared camera in the Equipment Sense-City

Objectives :

Reduce energy consumption in existing building

Strategies :

- In-situ evaluation of energy performances at *wall* and at *building scales* before and after renovation actions

*Identification of thermal characteristics using **inverse modelling technique (deterministic or probabilistic)***
[Ha 2020, De Simon 2018, Thébault 2018, Marshall 2017, Berger 2016, …]

- Reliable physical model to represent the thermal behaviour of the building

Inverse methods*: [Li 2018, Ogando 2017, Brouns 2016, Nassipoulos 2014, Manfren 2013,…]*

- Optimal control of the building equipments, *i.e* heating, ventilation, battery …

Deterministic and Stochastic algorithms *[Artiges 2020, Carpentier 2019, Nassiopoulos 2014, …]*

Context in Building Physics
- Limited number of sensors
- Many model parameters

Ill-posed inverse problem

Focus on local thermal behaviour (and *not global*)
- **goal-oriented model updating combining sensor and PDE**
- goal-oriented sensor placement

Goal-oriented inverse method applied to thermal building problems
[Djatouti 2020 a]

Objective :
Predict accurately a chosen Quantity of Interest (QoI) : Q(T)

- **Determine the model parameter p** such that it minimizes the functional

$$\mathcal{J}_Q(\mathbf{p}) = \frac{1}{2} r \left[Q\left(\mathbf{T}_1(\mathbf{p})\right) - Q\left(\mathbf{T}_2(\mathbf{p})\right) \right]^2$$

where the quantity of interest is calculated by two different ways :

1) From **physical model only**

$$\mathbb{C}(\mathbf{p})\dot{\mathbf{T}}_1 + \mathbb{K}(\mathbf{p})\mathbf{T}_1 = \mathbf{F}(\mathbf{p}) \quad ; \quad \mathbf{T}_1(t=0) = \mathbf{T}_0$$

2) From an **extrapolation of measurement** combining sensor and physical model

$$\begin{cases} \begin{bmatrix} \mathbb{C} & \mathbb{O} \\ \mathbb{O} & \mathbb{C} \end{bmatrix} \begin{Bmatrix} \dot{\mathbf{T}}_2 \\ \dot{\boldsymbol{\lambda}}_2 \end{Bmatrix} + \begin{bmatrix} \mathbb{K} & \mathbb{K} \\ \alpha \mathbf{B}^T \mathbb{G} \mathbf{B} & -\mathbb{K} \end{bmatrix} \begin{Bmatrix} \mathbf{T}_2 \\ \boldsymbol{\lambda}_2 \end{Bmatrix} = \begin{Bmatrix} \mathbf{F} \\ \alpha \mathbf{B}^T \mathbb{G} \mathbf{T}_{mes} \end{Bmatrix} \\ \mathbf{T}_2(t=0) = \mathbf{T}_0 \quad ; \quad \boldsymbol{\lambda}_2(t=t_f) = 0 \end{cases}$$

Derived from *Modified Constitutive Relation Error* *[Chouaki, Ladevèze, Proslier 96]*

Pro: the QoI does not necessarely need to be measured !

Goal-oriented inverse method applied to thermal building problems

Minimization of the QoI using gradient method with **adjoint framework**

$$\mathcal{J}_Q(\mathbf{p}) = \frac{1}{2} r \left[Q\left(\mathbf{T}_1(\mathbf{p})\right) - Q\left(\mathbf{T}_2(\mathbf{p})\right)\right]^2$$

- Rewrite as an optimisation problem under constrains and introduction of the Lagrangian:

$$\mathcal{L}_Q(\mathbf{T}, \mathbf{\Lambda}, \mathbf{p}) = \frac{1}{2} r \left[Q_1(\mathbf{T}_1(\mathbf{p})) - Q_2(\mathbf{T}_2(\mathbf{p})\right]^2 - \int_0^{t_f} \Lambda_1^T \left[\mathbb{C}\dot{\mathbf{T}}_1 + \mathbb{K}\mathbf{T}_1 - \mathbf{F}\right] dt - \int_0^{t_f} \Lambda_2^T \left[\mathbb{C}\dot{\mathbf{T}}_2 + \mathbb{K}\mathbf{T}_2 + \mathbb{K}\lambda_2 - \mathbf{F}\right] dt - \int_0^{t_f} \gamma_2^T \left[\mathbb{C}\dot{\lambda}_2 + \alpha \mathbf{B}^T \mathbb{G} \mathbf{B} \mathbf{T}_2 - \mathbb{K}\lambda_2 - \alpha \mathbf{B}^T \mathbb{G} \mathbf{T}_{mes}\right] dt$$

- Finding the saddle point lead to define supplementary adjoint fields:

  - $\mathbb{C}\dot{\mathbf{\Lambda}}_1 - \mathbb{K}\mathbf{\Lambda}_1 = -\mathbf{B}_Q \; ; \quad \mathbf{\Lambda}_1(\mathbf{x}, t = t_f) = 0$

  - $\begin{cases} \begin{bmatrix} \mathbb{C} & \mathbb{O} \\ \mathbb{O} & \mathbb{C} \end{bmatrix} \times \begin{Bmatrix} \dot{\gamma}_2 \\ \dot{\mathbf{\Lambda}}_2 \end{Bmatrix} + \begin{bmatrix} \mathbb{K} & -\mathbb{K} \\ -\alpha \mathbf{B}^T \mathbb{G} \mathbf{B} & -\mathbb{K} \end{bmatrix} \times \begin{Bmatrix} \gamma_2 \\ \mathbf{\Lambda}_2 \end{Bmatrix} = \begin{Bmatrix} 0 \\ \mathbf{B}_Q \end{Bmatrix} \\ \gamma_2(\mathbf{x}, t = 0) = 0 \; ; \quad \mathbf{\Lambda}_2(\mathbf{x}, t = t_f) = 0 \end{cases}$

Goal-oriented inverse method applied to thermal building problems

2 Forward-backward thermal problems involved in the inverse technique

$$\begin{cases} \begin{bmatrix} \mathbb{C} & \mathbb{O} \\ \mathbb{O} & \mathbb{C} \end{bmatrix} \begin{Bmatrix} \dot{\mathbf{T}}_2 \\ \dot{\boldsymbol{\lambda}}_2 \end{Bmatrix} + \begin{bmatrix} \mathbb{K} & \mathbb{K} \\ \alpha \mathbf{B}^T \mathbb{G} \mathbf{B} & -\mathbb{K} \end{bmatrix} \begin{Bmatrix} \mathbf{T}_2 \\ \boldsymbol{\lambda}_2 \end{Bmatrix} = \begin{Bmatrix} \mathbf{F} \\ \alpha \mathbf{B}^T \mathbb{G} \mathbf{T}_{mes} \end{Bmatrix} \\ \mathbf{T}_2(t=0) = \mathbf{T}_0 \quad ; \quad \boldsymbol{\lambda}_2(t=t_f) = 0 \end{cases}$$

$$\begin{cases} \begin{bmatrix} \mathbb{C} & \mathbb{O} \\ \mathbb{O} & \mathbb{C} \end{bmatrix} \times \begin{Bmatrix} \dot{\boldsymbol{\gamma}}_2 \\ \dot{\boldsymbol{\Lambda}}_2 \end{Bmatrix} + \begin{bmatrix} \mathbb{K} & -\mathbb{K} \\ -\alpha \mathbf{B}^T \mathbb{G} \mathbf{B} & -\mathbb{K} \end{bmatrix} \times \begin{Bmatrix} \boldsymbol{\gamma}_2 \\ \boldsymbol{\Lambda}_2 \end{Bmatrix} = \begin{Bmatrix} 0 \\ \mathbf{B}_Q \end{Bmatrix} \\ \boldsymbol{\gamma}_2(\mathbf{x}, t=0) = 0 \; ; \quad \boldsymbol{\Lambda}_2(\mathbf{x}, t=t_f) = 0 \end{cases}$$

In **thermal building applications**, **low number of dof** but **large time range**
➡ can be computationally expensive !!!

Idea:
Solve the forward-backward problems using « Proper Generalized Decomposition » *[Chinesta et al 2011]*

$$\mathbf{T}_m = \sum_{n=1}^{m} \mathbf{G}_n \times B_n(t) \quad ; \quad \boldsymbol{\lambda}_m = \sum_{n=1}^{m} \tilde{\mathbf{G}}_n \times \tilde{B}_n(t)$$

Technique based on separation of variables
[Djatouti 2020 b]

Goal-oriented inverse method applied to thermal building problems

Minimization of the QoI using gradient method with adjoint framework

$$\mathcal{J}_Q(\mathbf{p}) = \frac{1}{2} r \left[Q\left(\mathbf{T}_1(\mathbf{p})\right) - Q\left(\mathbf{T}_2(\mathbf{p})\right)\right]^2$$

❑ At each iteration of gradient method, only **update the model parameter** associated to the **highest component of the gradient** $\frac{\partial \mathcal{J}_Q}{\partial \mathbf{p}}$

$$\frac{\partial \mathcal{J}_Q}{\partial \mathbf{p}} = \frac{\partial \mathcal{L}_Q}{\partial \mathbf{p}} = r(Q_1 - Q_2)\left(\frac{\partial Q}{\partial \mathbf{p}}(\mathbf{T}_1) - \frac{\partial Q}{\partial \mathbf{p}}(\mathbf{T}_2)\right) - \int_0^{t_f} \boldsymbol{\Lambda}_1^T \left[\frac{\partial \mathbb{C}}{\partial \mathbf{p}}\dot{\mathbf{T}}_1 + \frac{\partial \mathbb{K}}{\partial \mathbf{p}}\mathbf{T}_1 - \frac{\partial \mathbf{F}}{\partial \mathbf{p}}\right] dt - \int_0^{t_f} \boldsymbol{\Lambda}_2^T \left[\frac{\partial \mathbb{C}}{\partial \mathbf{p}}\dot{\mathbf{T}}_2 + \frac{\partial \mathbb{K}}{\partial \mathbf{p}}\mathbf{T}_2 + \frac{\partial \mathbb{K}}{\partial \mathbf{p}}\boldsymbol{\lambda}_2 - \frac{\partial \mathbf{F}}{\partial \mathbf{p}}\right] dt - \int_0^{t_f} \boldsymbol{\gamma}_2^T \left[\frac{\partial \mathbb{C}}{\partial \mathbf{p}}\dot{\boldsymbol{\lambda}}_2 - \frac{\partial \mathbb{K}}{\partial \mathbf{p}}\boldsymbol{\lambda}_2\right] dt$$

Gradient of the functional fully computable !

Full details of the goal inverse technique given in *[Djatouti 2020 a]*.

Application to thermal building problems in the Sense-City Equipment

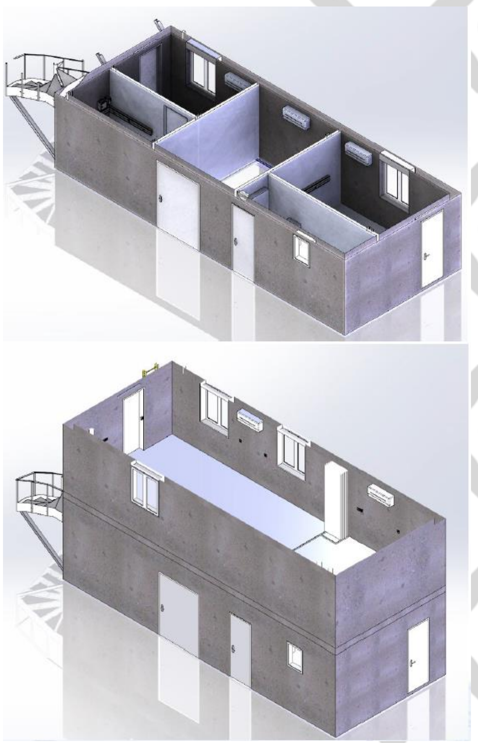
Sense-City Equipment

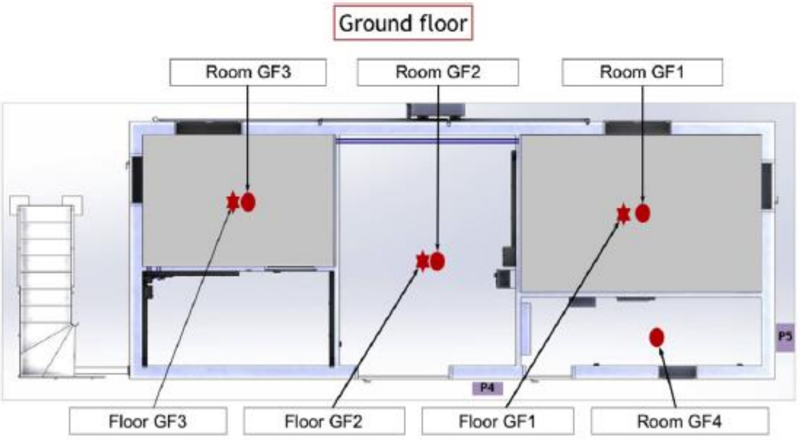
- Small district (400m2) at real scale
- Controlled conditions (temperature, humidity, sun, …) using climatic chamber
- Study of the thermal behaviour of the building during a winter climate and Paris 2003 heat wave

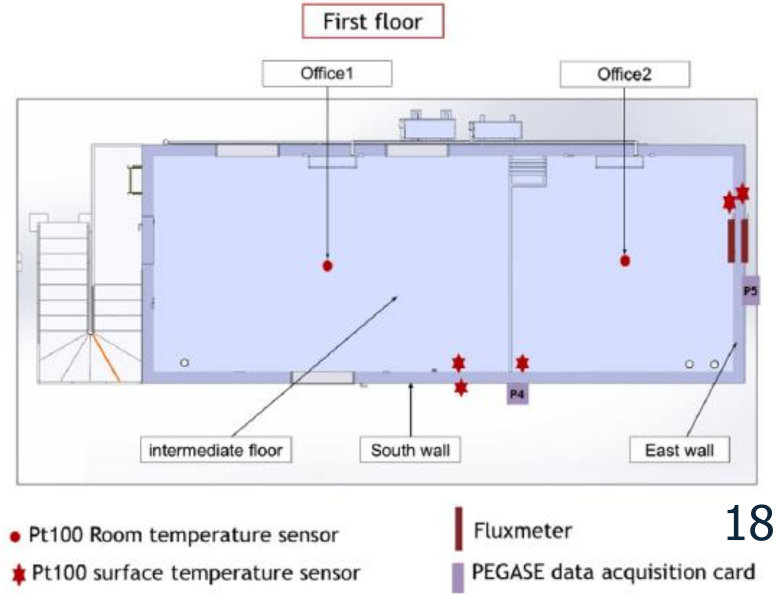
[Djatouti 2020 c]

Building of Sense-City

- Reinforced concrete building with two floors
- Air renewal by forced mechanical ventilation
- Controlled electric convecter using connected power socket
- *Definition of different occupation scenarios at the ground floor and the first floor*
- Building equipped with many sensors



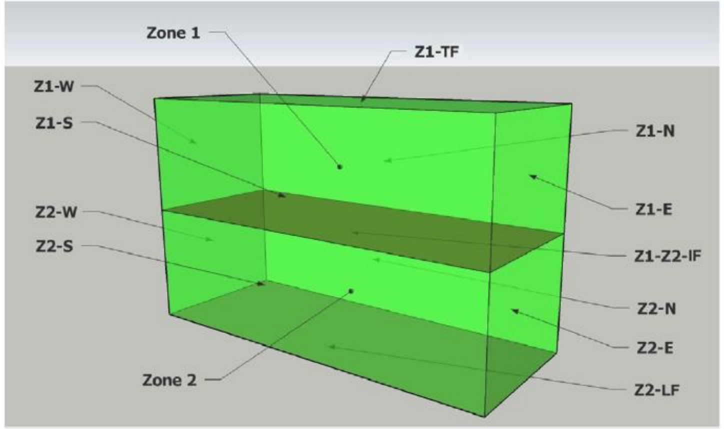




Application to thermal building problems in the Sense-City Equipment

Thermal physical model

Use of a two-zone thermal model



- 1 dof per zone
- 11 dof per envelopes

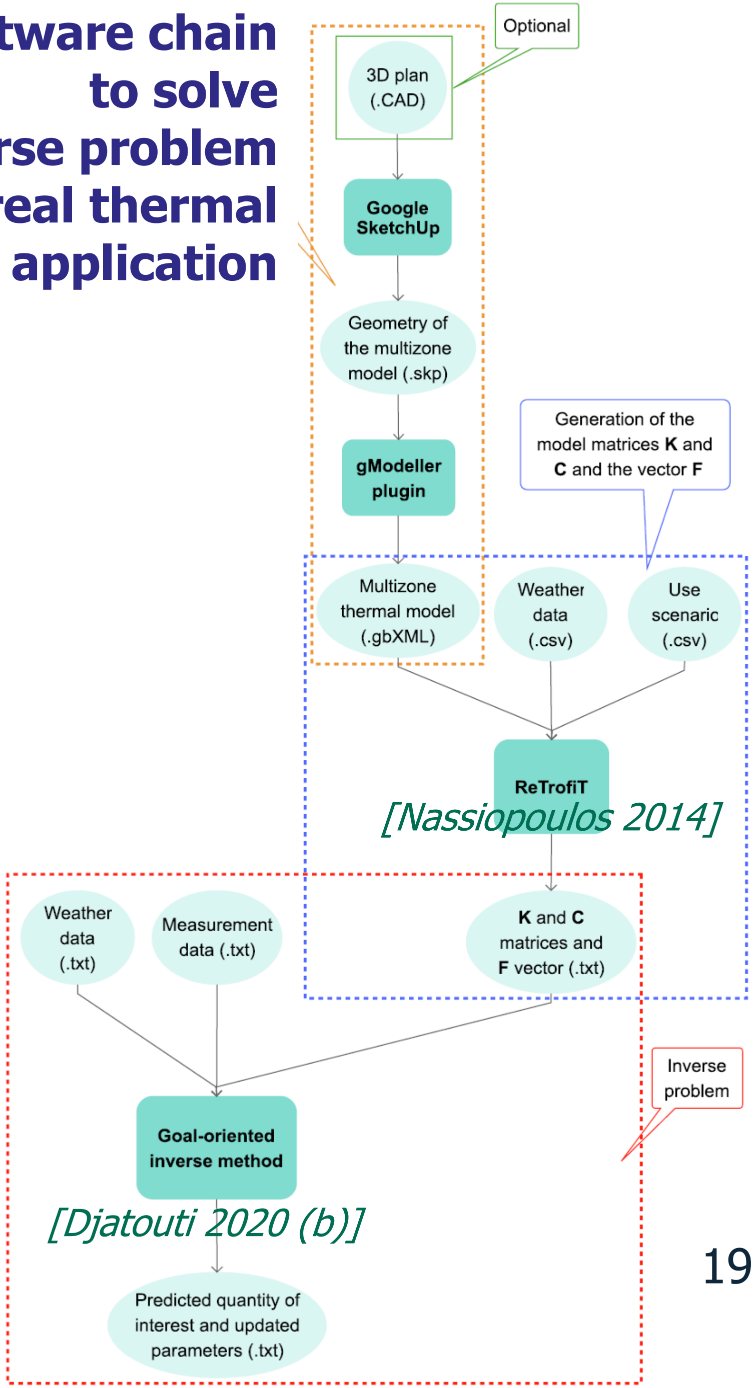
→123 degrees of freedom

List of model parameters

Component	Parameter	Unit	Initial value
Zone 1	C_{Z_1}	(J/K)	1.4×10^5
	$c_a R_1$	(W/K)	18
Zone 2	C_{Z_2}	(J/K)	1.4×10^5
	$c_a R_2$	(W/K)	21
Walls	k_W	$(W/(m.K))$	1.4
	c_W	$(J/(m^3.K))$	18×10^5
Top floor	k_{TF}	$(W/(m.K))$	2
	c_{TF}	$(J/(m^3.K))$	25×10^5
Intermediate floor	k_{IF}	$(W/(m.K))$	2
	c_{IF}	$(J/(m^3.K))$	25×10^5
Lower floor	k_{LF}	$(W/(m.K))$	2
	c_{LF}	$(J/(m^3.K))$	25×10^5
	h_s	$(W/(m^2.K))$	5
Interior heat exchange	h_i	$(W/(m^2.K))$	7.7
Exterior heat exchange	h_e	$(W/(m^2.K))$	24

→ 14 model parameters

Software chain to solve the inverse problem in real thermal building application



Application to thermal building problems in Sense-City

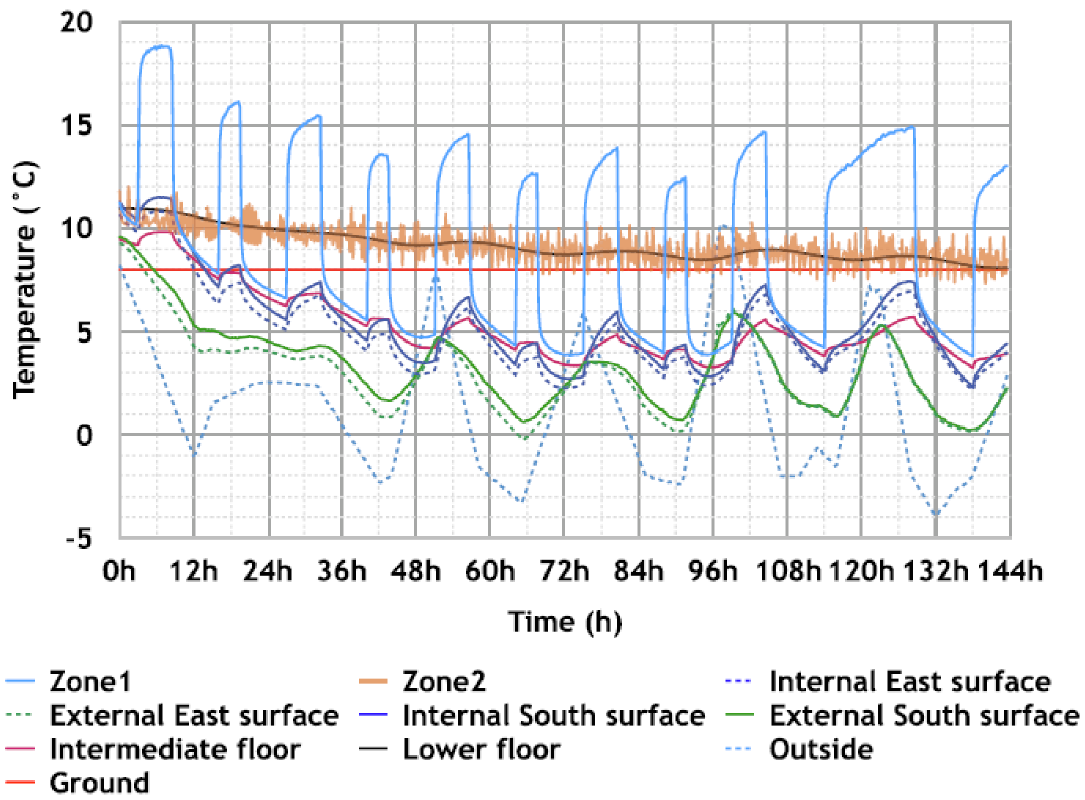
Study 1 : Reliable prediction of QoI during a south of France winter climate

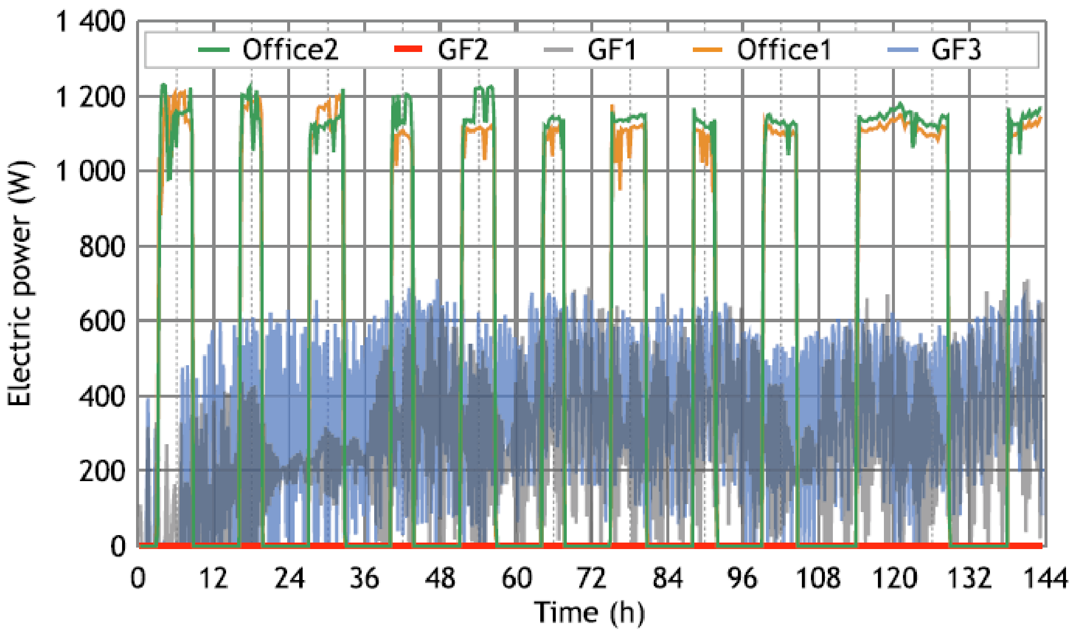
Occupation scenarios

- *Ground floor : electrical heaters in frost-protection mode*
- *First floor : electrical heaters switched-on at fixed hours*

All data available in « Data in Brief » article *[Djatouti 2020 c]*

Sensor Outputs





Used power by heaters

Application to thermal building problems in Sense-City

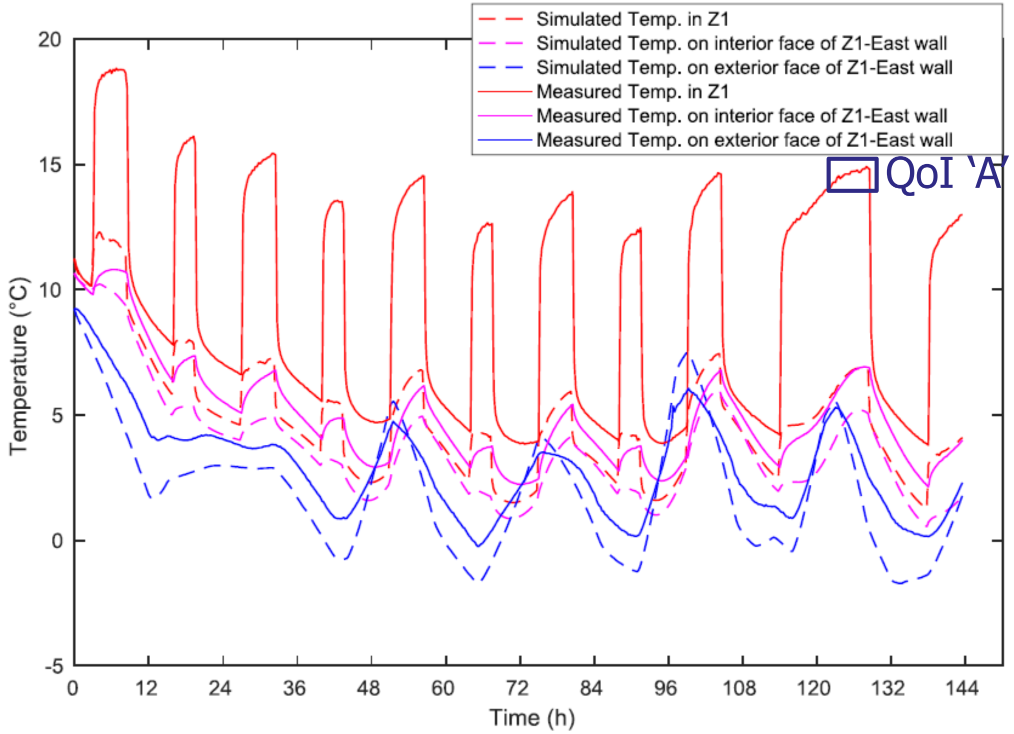
Study 1 : Reliable prediction of QoI during a south of France winter climate

Definition of a quantity of interest

Q^A : Temperature in first floor at the end of a heating period

$$Q^A = \frac{1}{t_2^A - t_1^A} \int_{t_1^A}^{t_2^A} T_{Z_1}(t)dt \quad \text{where } t_1^A = 125\ h \text{ and } t_2^A = 128\ h.$$

No model updating



- Temperature in Zone 1 strongly underestimated

$$Q_{sim}^A = 6.8°C\ (Q_{meas}^A = 14.7°C)$$

High gap between simulation and measurement !

Need of model updating techniques to better represent the temperature in the first floor during a winter climate

Application to thermal building problems in Sense-City

Study 1 : Reliable prediction of QoI during a south of France winter climate

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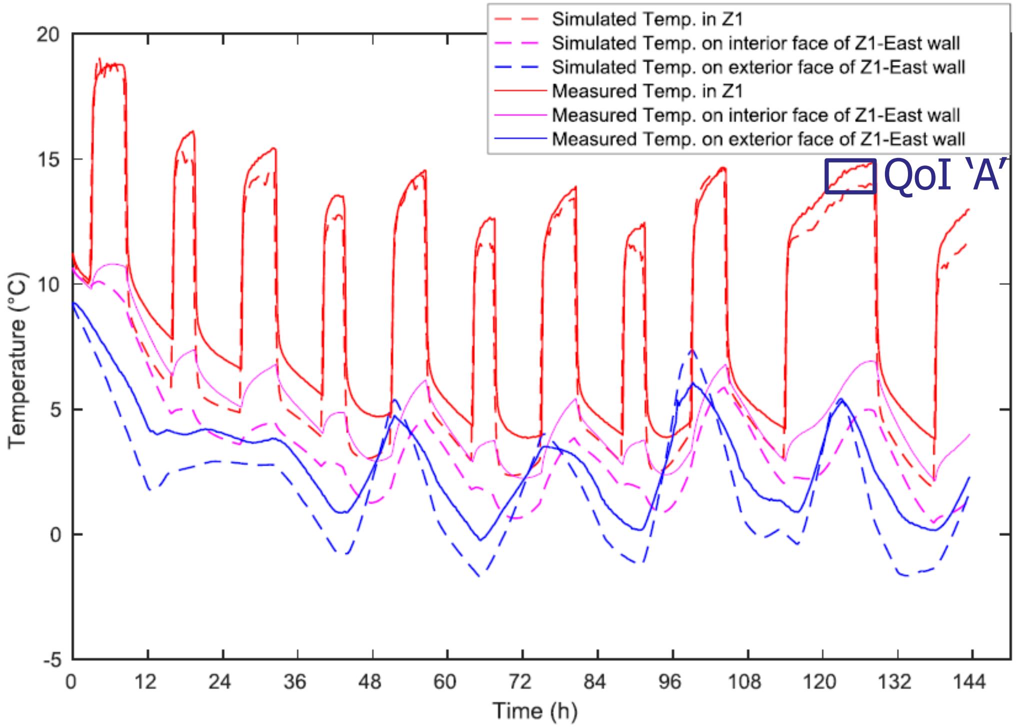
$$Q^A = \frac{1}{t_2^A - t_1^A} \int_{t_1^A}^{t_2^A} T_{Z_1}(t)dt \quad \text{where } t_1^A = 125\ h \text{ and } t_2^A = 128\ h.$$

After goal-oriented model updating



- **Only 2 parameters updated** by the goal-oriented inverse technique (Most sensitive parameters !)
  - Internal exchange coefficient : $h_i = 1.5\ W/(K.m^2)$
  - Thermal heat capacity of the wall $c_m = 20 \times 10^5\ J/(m^3.K)$
- Better fit between simulation and measurement for the QoI (Temperature in first floor)

$$Q^A_{updated} = 13.9°C\ (Q^A_{meas} = 14.7°C)$$

- Other temperatures are not well-predicted

→ expected behaviour of the proposed local inverse technique

Application to thermal building problems in Sense-City

Study 1 : Reliable prediction of QoI during a south of France winter climate

Definition of a quantity of interest

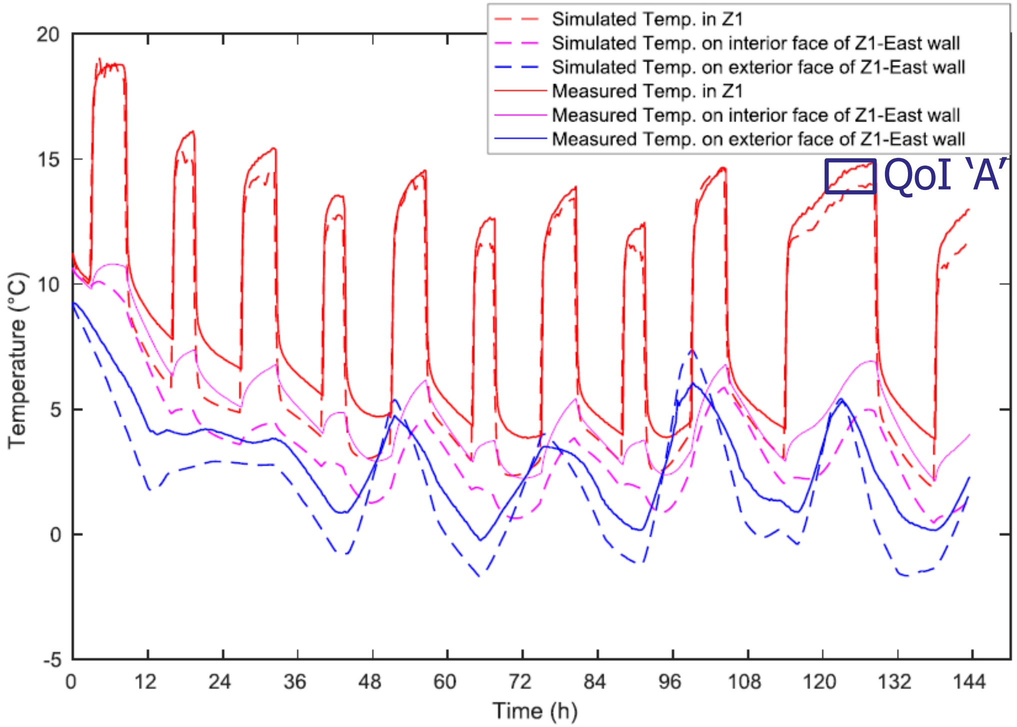
Q^A : Temperature in first floor at the end of a heating period

$$Q^A = \frac{1}{t_2^A - t_1^A} \int_{t_1^A}^{t_2^A} T_{Z_1}(t)dt \quad \text{where } t_1^A = 125\ h \text{ and } t_2^A = 128\ h.$$

Validation of the updated parameter value using a stationary test in Sense-City

$$h_i^{exp} = 2.1\ W/(m^2.K)$$

After goal-oriented model updating



- **Only 2 parameters updated** by the goal-oriented inverse technique (Most sensitive parameters !)
  - Internal exchange coefficient : $h_i = 1.5\ W/(K.m^2)$
  - Thermal heat capacity of the wall $c_m = 20 \times 10^5\ J/(m^3.K)$

- Better fit between simulation and measurement for the QoI (Temperature in first floor)

$$Q^A_{updated} = 13.9°C\ (Q^A_{meas} = 14.7°C)$$

- Other temperatures are not well-predicted

→ expected behaviour of the proposed local inverse technique

Application to thermal building problems in Sense-City

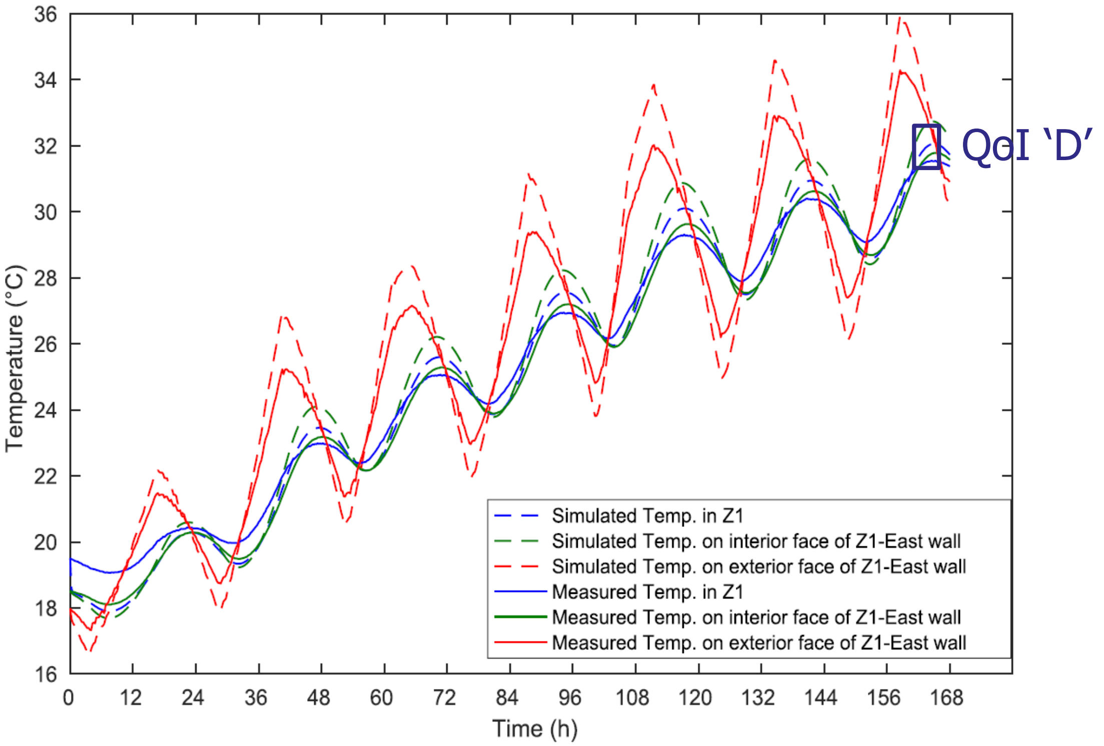
Study 2 : Reliable prediction of QoI during Paris 2003 heatwave climate

Definition of a quantity of interest

QA : Temperature in first floor during the three warmest hours

$$Q^D = \frac{1}{t_2^D - t_1^D} \int_{t_1^D}^{t_2^D} T_{Z_1}(t)dt \quad \text{where } t_1^D = 164\ h \text{ and } t_2^D = 167\ h.$$

No model updating



- Accurate prediction of the temperature in Zone 1 using initial set of model parameters

$$Q_{sim}^D = 32.0°C\ (Q_{meas}^D = 31.5°C)$$

- Goal-oriented inverse technique automatically detects that there is **no need to update model parameter**

→ inverse process stops at first iteration

- Internal exchange coefficient h_i is not influent in this heatwave climate scenario

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Conclusions & Perspectives

Conclusions

➢ **Inverse deterministic approaches** using **gradient method** and **adjoint framework** for fast identification of model parameters

➢ **Urban applications with real sensor outputs**

Global model updating techniques

- *Determination of a large number of model parameters*

to get an ***overall good agreement between sensor and simulation***

- *Many sensor outputs required*

Local model updating technique

- **Accurate prediction of a quantity of interest**

by updating few model parameters

- Limited number of sensor needed
- Potential reduction of computation time

Future works on model calibration

Earth construction in Sense-City

- *PhD Hadi Nasser* « **Multi-fidelity approaches** & **Inverse problem** with **uncertainty quantification**: identification of thermal resistance of bio-sourced wall »
Project ANR RESBIOBAT
in collaboration with G. Perrin, R. Chakir, S. Demeyer

- Model calibration of masonry bridge using **static, dynamic and vibration testing** & Development of **damage detection technique with low instrumentation**
Project IA2: Univ. Eiffel & Sixense (Vinci)
B. Streichenberger, G. Perrin, D. Siegert, E. Bourgeois, …, F. Bourquin

- Calibration of **physical models at district scale** and selection of **adapted urban planning by virtual testing**
Application to Urban Heat Island
Project PRRD ICU: Univ. Eiffel & Resallience - Post-doc Nacer Sellila

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ACKNOWLEDGEMENTS

V. Le Corvec
(NECS)

D. Siegert
(Univ. Eiffel)

B. Rosic
(Univ. Twente/TU Braunschweig)

Z. Djatouti
(PhD)

L.M. Cottineau
(Univ. Eiffel)

P.-E. Charbonnel
(CEA Saclay)

X. Chapeleau
(Univ. Eiffel)

V. Le Corvec
(NECS)

L. Chamoin
(ENS Paris-Saclay)

F. Bourquin
(Univ. Eiffel)

P. Chatellier
(Univ. Eiffel)

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(Sixense Engineering)

sense CITY

THANK YOU FOR YOUR ATTENTION !

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