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Integrated Structural Health Monitoring with Real-time Data Assimilation and Hybrid Twins

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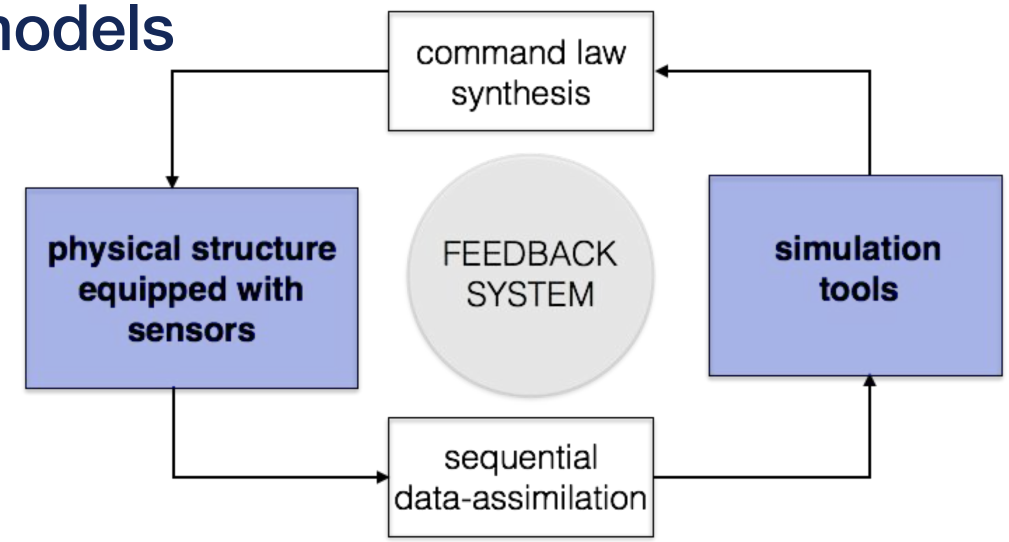
Context

Dynamic Data Driven Application Systems (DDDAS)

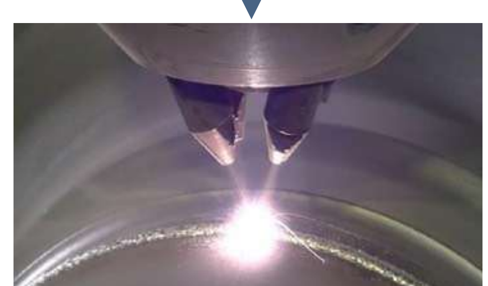
- continuous integration of sensor data into numerical models
- customized digital twin to monitor evolving systems
  enhanced diagnosis, prognosis & control (anticipate, decide)
- exploitation at best of all knowledge (models & data)
- key enabler of next-generations technologies
- economical & societal impact
  increased performance & reliability



Dynamic Data-Driven Application Systems (DDDAS)

assisted surgery

building performance



manufacturing

integrated simulation-based SHM

renewable energy

transportation

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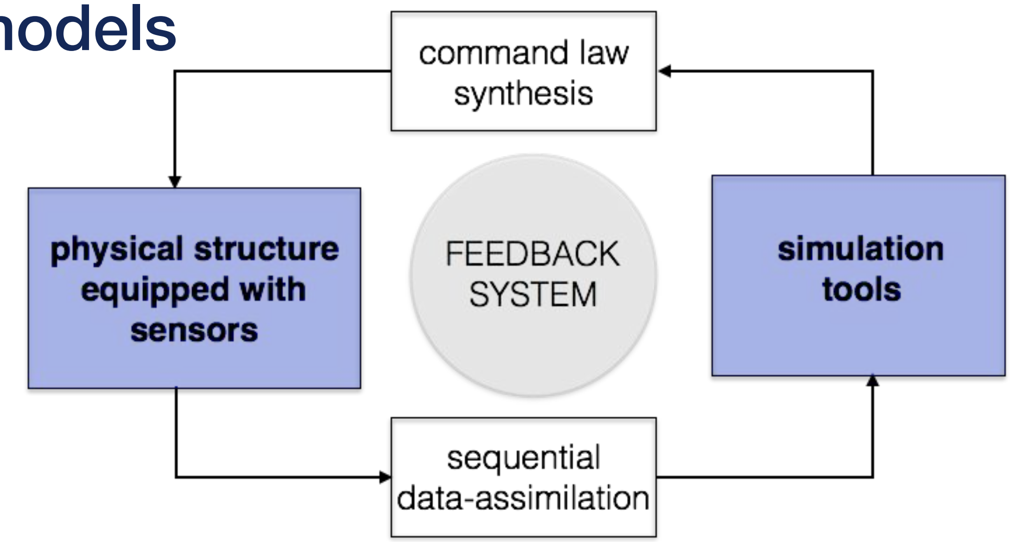
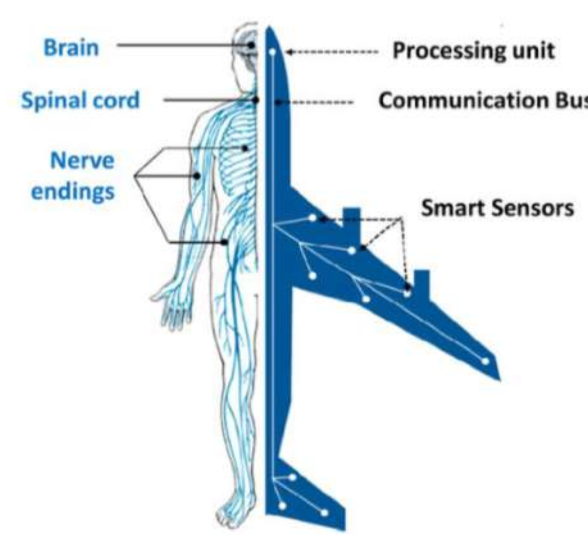


integrated simulation-based SHM

SMART ENGINEERING STRUCTURES

- online monitoring of the integrity (damage detection/control)
- anticipated action during service

enhanced durability and performance
operation in degraded mode
optimized maintenance

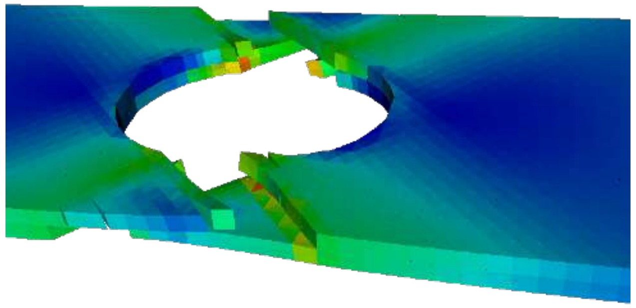


renewable energy

transportation

Challenges & Objectives

- **Challenges for real-life engineering applications**
  - complex systems (nonlinear, multi-scale/physics, large…)
  - limited amount of expensive/heterogeneous/indirect/noisy data
  - uncertain environment, biased models of the system behavior



- **Objectives**
  - numerical methods dedicated to on-the-fly sequential data assimilation & control
  - performance in terms of robustness & accuracy (safe decision-making)
  - compatibility with advanced sensing & portability (edge computing)

- **Strategy**
  - use of simplified *a priori* physics-based models with ROM
  - effective correction of model ignorance (data-based enrichment) ⟶ **hybrid twins** [Chinesta *et al.* 2020]
  - **bias-aware** data assimilation & control techniques

good prior knowledge + limited amount of data

⟶ *(multidisciplinary) strategies designed from the mCRE concept*

Outline

- **Illustrated introduction to hybrid twins**
- **mCRE framework for data assimilation**
- **Sequential strategy coupling mCRE with Kalman filtering**
  Application to the online control of shaking table tests on large-scale damageable concrete buildings
- **On-the-fly adaptive modeling for enhanced computational efficiency**
  Application to the design of smart structures equipped with embedded distributed optic fiber sensors

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Outline

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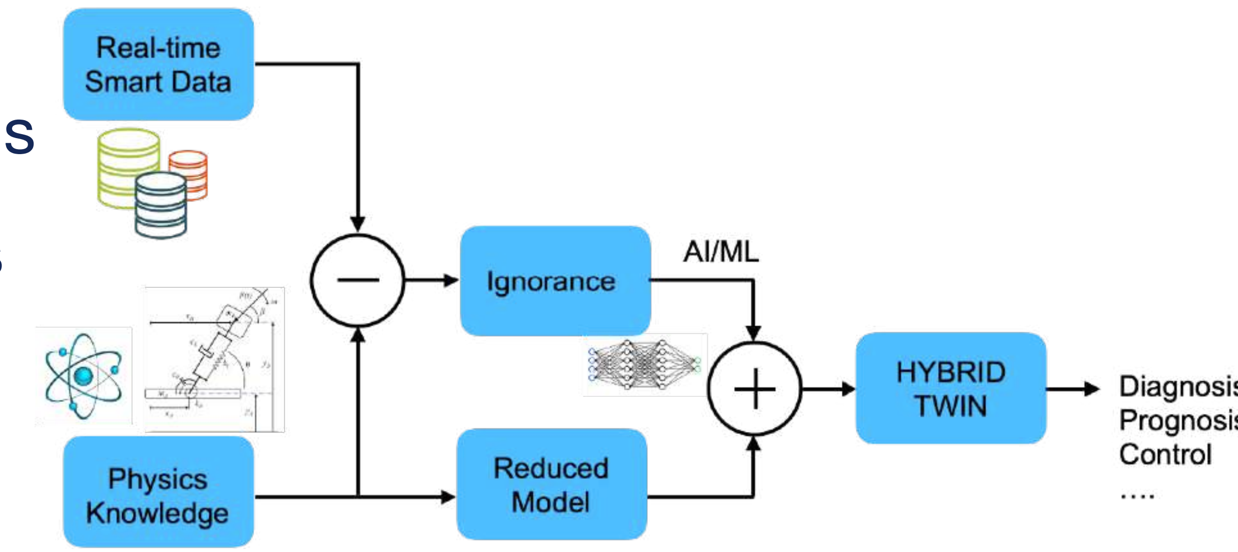
Basics on Hybrid Twins

uncertain environment/behavior of complex systems

➡ use of *a priori* physics-based (biased) models
e.g. with ROM

➡ data-based correction of model ignorance



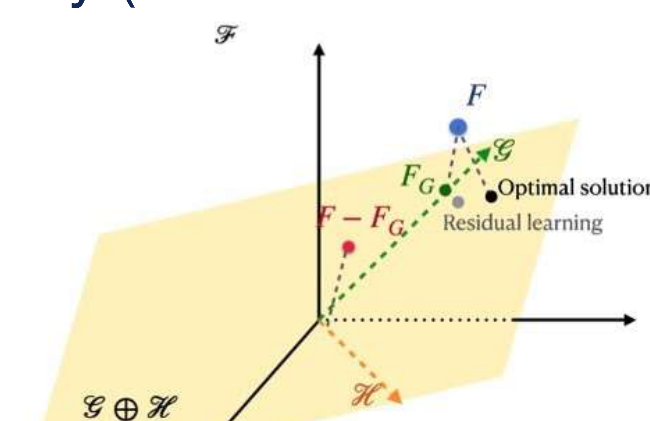
$\mathcal{G}$ Physics-based model $+$ $\mathcal{H}$ Data-based model → Combined model

$$\tilde{F} = \operatorname{argmin}_{\hat{F} \in \mathcal{G} \oplus \mathcal{H}} \|F - \hat{F}\| \qquad \mathcal{G} \oplus \mathcal{H} = \{F_{\mathcal{G}} + F_{\mathcal{H}} : F_{\mathcal{G}} \in \mathcal{G}, F_{\mathcal{H}} \in \mathcal{H}\}$$

Many advantages:
- versatility compared to purely data-driven approaches
- resilience to data overfitting / needs less data
- performance with conditions outside training bounds (extreme events)
- interpretability (understanding), explainability (UQ in decision-making),…

BUT the implementation should avoid sub-optimality

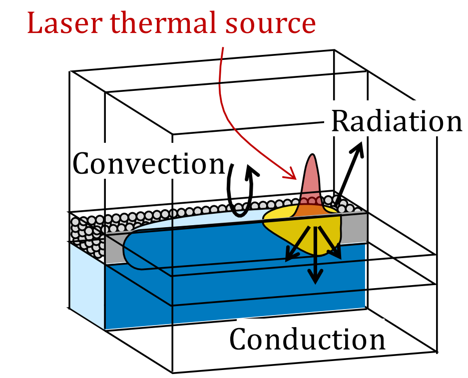
- ensure orthogonality/complementarity
- ensure bias-aware data assimilation & control



residual learning
(learning $F - F_{\mathcal{G}}$ in $\mathcal{H}$)

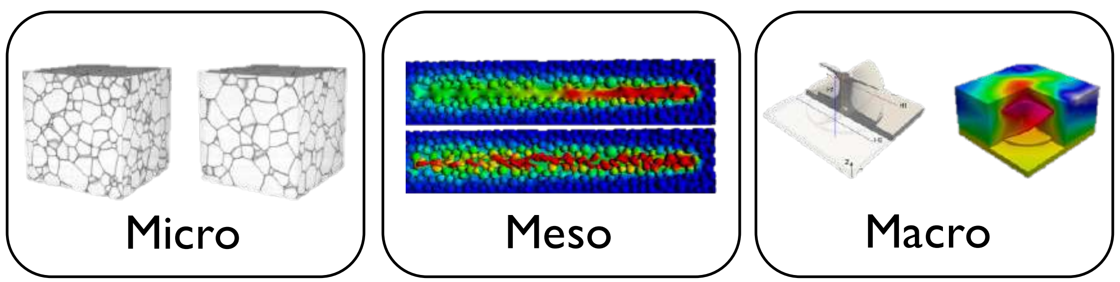
Illustration: Real-Time Monitoring in AM

■ Transient thermal analysis in LPBF processes



GOALS:

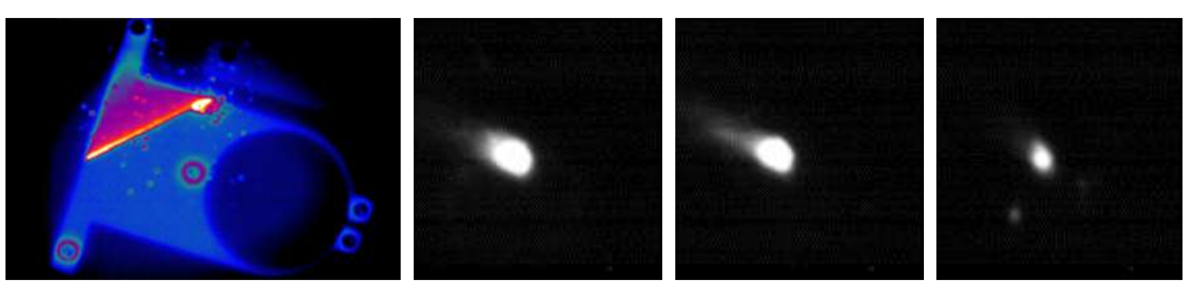
- **at melt pool scale:** predict the size of the melt pool depending on the laser trajectory
- **at layer scale:** predict cooling rates and hot points to assess residual stresses



Credits : Cemef, MSSMAT, LMT

complex multiphysics, multiscale phenomena

➡ reduced complexity (simplified model & ROM)
large model bias



thermography data from NIST
Nat. Institute of Standards & Technology (www.nist.gov)

➡ rich (noisy) data to enrich the physics model
selection of relevant data

coarse initial model + rich data ⟶ Parametrized Background Data Weak (PBDW) [Maday *et al.* 2015]

PBDW Framework

Basic formulation

Non-intrusive / reduced-basis / variational approach

Key idea: seek an approximation of the true state by employing projection-by-data

$$u_{N,M} = z_{N,M} + \eta_{N,M}$$

physics-based estimate: computed from ROM *on a surrogate model*

data-based correction: informed by experimental observations

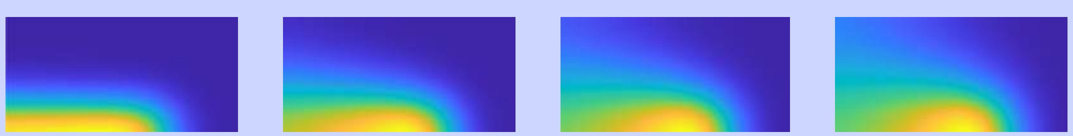
Inputs & Outputs (OFFLINE)

- Parametrized best-knowledge model (PDE)

$$\rho_{eq} c(\frac{\partial u}{\partial t} + \mathbf{v} \cdot \nabla u) = \lambda_{eq} \Delta T + r$$

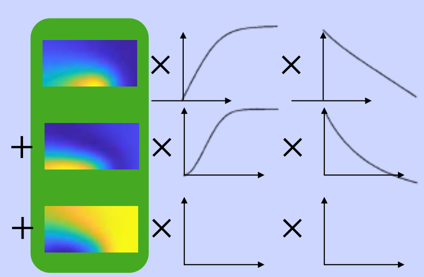
- Parametric domain: $\mu = \lambda_{eq} \in D$

$\longrightarrow$ *manifold of solutions* $M^{bk} = \{u^{bk,\mu} | \mu \in D\}$



- Space/(time)/parameter decomposition

$$\sum_{n=1}^{N} \zeta_n(x) \times \lambda_n(t) \times \alpha_n(\mu)$$



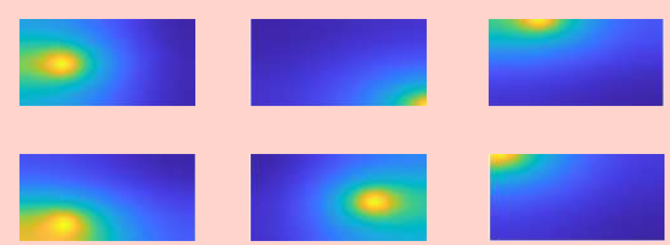
$\hookrightarrow$ **background space** $Z_N = span\{\zeta_n\}_{n=1}^{M}$

- Hilbert space (with norm & inner product)
- Positions of sensors: x_m^{obs}
- Observation functionals

$$l_m(v) = C(x_m^{obs}) \int v(x) e^{-\frac{\|x - x_m^{obs}\|^2}{2r_w^2}} dx$$

- Riesz representers: $q_m = R_U l_m$

$$(q_m, v) = l_m(v) \; \forall v \in U$$



$\hookrightarrow$ **update space** $U_M = span\{q_m\}_{m=1}^{M}$

PBDW Framework

Basic formulation

$$u_{N,M} = z_{N,M} + \eta_{N,M}$$

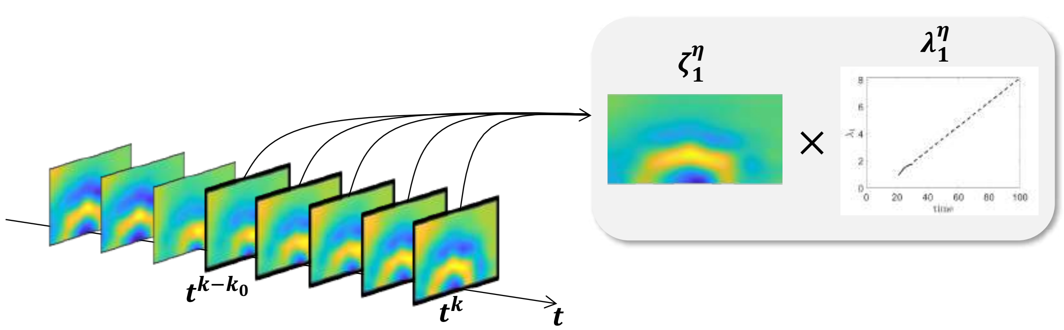
$$\sum_{n=1}^{N} a_n \zeta_n \in Z_N \qquad \sum_{m=1}^{M} b_m q_m \in U_M$$

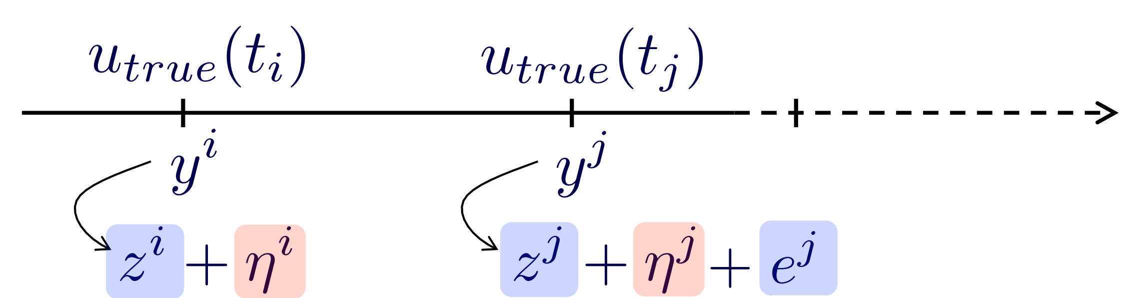
Implementation (ONLINE)

$$(z_{N,M}, \eta_{N,M}) = \underset{z \in Z_N, \eta \in U_M}{argmin} \left(\underbrace{\epsilon \|\eta\|^2}_{\text{modeling error}} + \underbrace{\|L(z+\eta) - y^{obs}\|_2^2}_{\text{data misfit}} \right)$$

$$\begin{bmatrix} \mathbb{A} + \epsilon M \mathbb{I} & \mathbb{B} \\ \mathbb{B}^T & 0 \end{bmatrix} \begin{pmatrix} b \\ a \end{pmatrix} = \begin{pmatrix} y^{obs} \\ 0 \end{pmatrix} \qquad \begin{aligned} A_{i,j} &= (q_i, q_j) \\ B_{i,j} &= (\zeta_i, q_j) \end{aligned}$$

- full error convergence analysis provided [Gong *et al.* 2019]
- embedded optimal data management (stability-greedy algorithm, cf. GEIM)
  - **Step 1**: optimal sensor placement (description of the background space): max $\beta_{N,M} = \inf_{\eta \in U_M} \sup_{z \in Z_N} \frac{|(z,\eta)|}{\|z\|.\|\eta\|}$
  - **Step 2**: farthest first traversal to get a good approximation of η: $x_{m+1}^{obs} = \underset{x \in X}{argmax} \min_{i=1:m} \|x - x_i^{obs}\|$
- extension to parametrized time-dependent problems [Haïk *et al.* 2023]

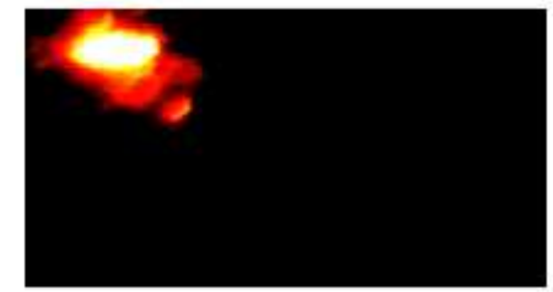




Monitoring at the Layer Scale

Experimental data

- Thermography measurements from NIST [Molnar *et al.* 2021]
- High-frequency global camera ($f = 2000Hz$)



Surrogate (background) model

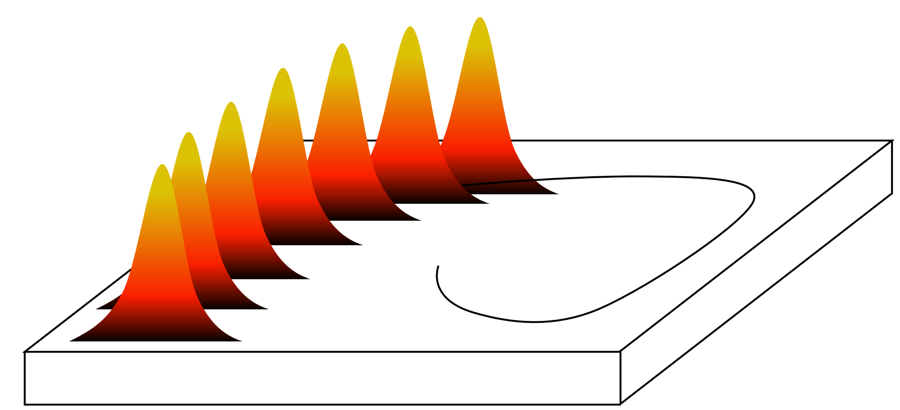
- 2D analytical thermal model from the FLASH method [Ettaieb *et al.* 2021]

Effect of a single flash

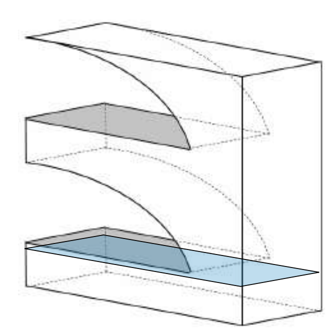
$$T_f(t,r,\alpha,\epsilon) = \frac{2AQ}{\epsilon\sqrt{\pi^3(t)}} \frac{1}{R^2+8\alpha(t)} e^{-\frac{2r^2}{R^2+8\alpha(t)}}$$

Convolution along the trajectory $s(t)$

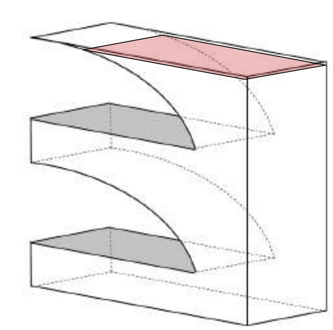
$$T(t,x) = \sum_i (\gamma_i \times \Delta t).T_f(t - i\Delta t, \|x - s_i\|_2, R)$$



- Conductivity λ plays a major role in the t° profile



Layer on a massive part
(built on previous molten layer)

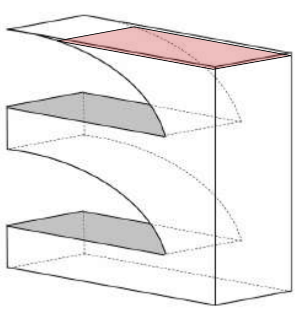


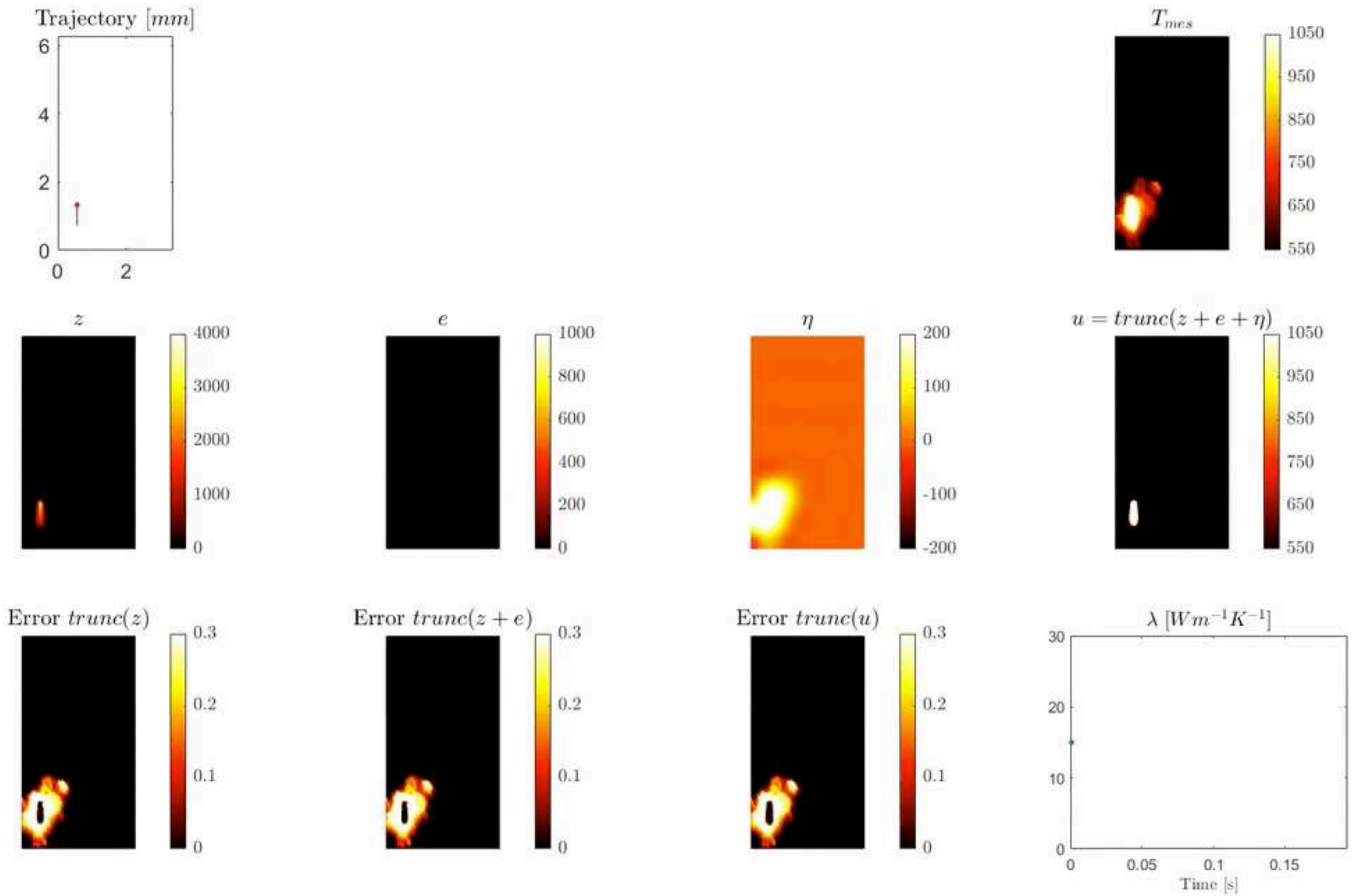
Layer on a overhang
(mostly built on powder)

DDDAS objective: monitor the lasing trajectory to prevent residual stresses

Monitoring at the Layer Scale

Results





Monitoring in real-time using parallel computation: $t_{est} \sim 5 - 10ms$

Ongoing work: learn the bias from AI

(Physics-enhanced ML, PBDW+DeepONets [Massala *et al.* 2026])

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mCRE Framework

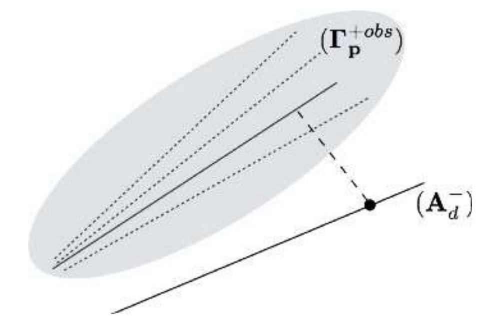
[Ladevèze & Chouaki 1999]

Reliability of information (various error sources)

The problem is split in :
- reliable info (equilibrium,…) $\longrightarrow$ enforced in the process (admissibility)
- unreliable info (material behavior, BCs, sensor values,…)

Cost function:
$$\mathcal{E}^2_{mCRE}(\hat{\mathbf{u}}, \hat{\sigma}; \mathbf{p}) = \underbrace{\mathcal{E}^2_{CRE}(\hat{\mathbf{u}}, \hat{\sigma}; \mathbf{p})}_{\text{modeling error term}} + \underbrace{\frac{\alpha}{2}(\mathbf{d}(\hat{\mathbf{u}}) - \mathbf{d}_{obs})^T \mathbb{G}^{-1}_{obs}(\mathbf{d}(\hat{\mathbf{u}}) - \mathbf{d}_{obs})}_{\text{distance to observations}}$$

$$\mathbf{p}_{sol} = argmin_{\mathbf{p}\in\mathcal{P}} \left[\min_{(\hat{\mathbf{u}},\hat{\sigma})\in(\mathbf{A}_d^-)} \mathcal{E}_{mCRE}(\hat{\mathbf{u}}, \hat{\sigma}; \mathbf{p}) \right]$$



- regularization from physics with various applications
  variational primal-dual formulation [Chavent et al. 1999] , *Kohn-Vogelus-type functional* [Kohn & Lowe 1988]
- nice mathematical properties (enhanced convexity, spatial localization of defects…)
- robustness with noisy/corrupted data [Feissel & Allix 2007, Ben Azzouna *et al.* 2015]
- explicit (distributed) modeling error to drive/learn the model complexity

Link with Bayesian inf.: (Tarantola's framework)
$$\pi(\mathbf{d}_{obs}|\mathbf{p}) = C_1.e^{-\frac{1}{2}(\mathbf{d}_{obs}-\mathbf{d}(\hat{\mathbf{u}}(\mathbf{p})))^T\mathbb{G}^{-1}_{obs}(\mathbf{d}_{obs}-\mathbf{d}(\hat{\mathbf{u}}(\mathbf{p})))}.\underbrace{e^{-\frac{\mathcal{E}^2_{CRE}(\hat{\mathbf{u}},\hat{\sigma};\mathbf{p})}{\alpha}}}_{\pi_{mod}}$$

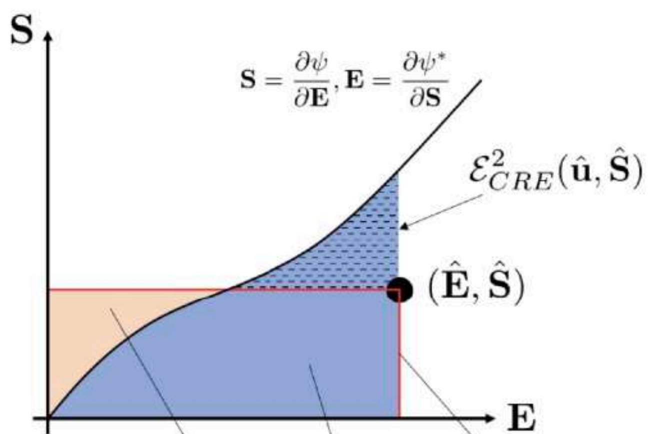
mCRE Framework

■ CRE measure [Ladevèze & Pelle 2004, Ladevèze & LC 2015]

$$\mathbf{S} = \frac{\partial \psi}{\partial \mathbf{E}} \longrightarrow \boxed{\mathcal{E}^2_{CRE}(\hat{\mathbf{u}}, \hat{\mathbf{S}}) = \int_\Omega \left(\psi(\hat{\mathbf{u}}) + \psi^*(\hat{\mathbf{S}}) - \hat{\mathbf{S}} : \mathbf{E}(\hat{\mathbf{u}}) \right)}$$

$$\psi^*(\hat{\mathbf{S}}) = \sup_{\mathbf{E}} \left[\hat{\mathbf{S}} : \mathbf{E} - \psi(\mathbf{E}) \right]$$

Legendre-Fenchel dual potential



$$\mathcal{E}^2_{CRE}(\hat{\mathbf{u}}, \hat{\mathbf{S}}) = \int_\Omega \left(\psi(\hat{\mathbf{u}}) + \psi^*(\hat{\mathbf{S}}) - \boxed{\hat{\mathbf{S}} : \mathbf{E}(\hat{\mathbf{u}})} \right)$$

- **Case of quadratic potentials**

$$\psi(\mathbf{E}(\hat{\mathbf{u}})) = \frac{1}{2}\mathbf{E}(\hat{\mathbf{u}}) : \mathbf{K} : \mathbf{E}(\hat{\mathbf{u}}) \qquad \psi^*(\hat{\mathbf{S}}) = \frac{1}{2}\hat{\mathbf{S}} : \mathbf{K}^{-1} : \hat{\mathbf{S}}$$

$$\mathcal{E}^2_{CRE}(\hat{\mathbf{u}}, \hat{\mathbf{S}}) = \frac{1}{2}\int_\Omega (\hat{\mathbf{S}} - \mathbf{K}\mathbf{E}(\hat{\mathbf{u}})) : \mathbf{K}^{-1} : (\hat{\mathbf{S}} - \mathbf{K}\mathbf{E}(\hat{\mathbf{u}}))$$

➡ related to sym. Bregman divergence (discrepancy metric)

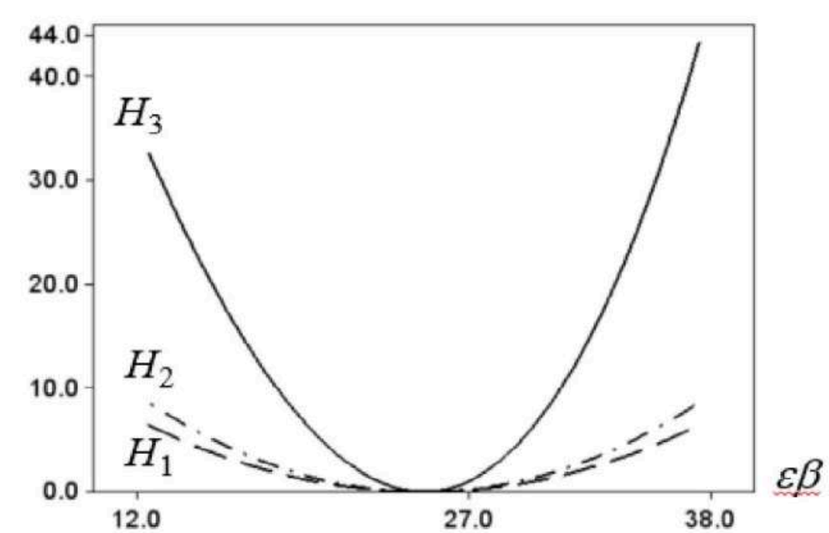
S. Andrieux, Bregman divergences for physically informed discrepancy measures for learning and computation in thermomechanics, *Comptes Rendus Mécanique*, **351**:59-81 (2023)

$$-u'' + \alpha^2 u + \varepsilon\beta u^3 = 0, \quad u(0) = 0, u'(1) = C$$

$$H_1(\varepsilon\beta) = \frac{\alpha^2}{2}\int_0^1 (u(\varepsilon\beta) - u(\varepsilon\beta_0))^2 \mathrm{d}x,$$

$$H_2(\varepsilon\beta) = \frac{1}{2}\int_0^1 \left[(u'(\varepsilon\beta) - u'(\varepsilon\beta_0))^2 + \alpha^2(u(\varepsilon\beta) - u(\varepsilon\beta_0))^2 + \varepsilon\beta(u(\varepsilon\beta) - u(\varepsilon\beta_0))^4 \right] \mathrm{d}x$$

$$H_3(\varepsilon\beta) = \frac{1}{2}\int_0^1 \left[(u'(\varepsilon\beta) - u'(\varepsilon\beta_0))^2 + \alpha^2(u(\varepsilon\beta) - u(\varepsilon\beta_0))^2 + \varepsilon\beta(u(\varepsilon\beta) - u(\varepsilon\beta_0))(u^3(\varepsilon\beta) - u^3(\varepsilon\beta_0)) \right] \mathrm{d}x.$$



Implementation - Elasticity case

- **Step 1 (localization):** define $\mathcal{F}(\mathbf{p}) = \min_{(\hat{\mathbf{u}},\hat{\sigma})\in(\mathbf{A}_d^-)} \mathcal{E}_{mCRE}(\hat{\mathbf{u}},\hat{\sigma};\mathbf{p})$

⟶ Lagrangian functional $\mathcal{L}(\hat{\mathbf{u}},\hat{\sigma},\boldsymbol{\lambda};\mathbf{p}) = \mathcal{E}^2_{mCRE}(\hat{\mathbf{u}},\hat{\sigma};\mathbf{p}) - \left[\int_\Omega \hat{\sigma} : \epsilon(\boldsymbol{\lambda}) - \int_\Omega \mathbf{f}_d \cdot \boldsymbol{\lambda} - \int_{\partial_2\Omega} \mathbf{F}_d \cdot \boldsymbol{\lambda}\right]$

$\mathbf{K}\epsilon(\mathbf{v})$(duality)

⟶ $\mathcal{L}(\mathbf{U},\mathbf{V},\boldsymbol{\Lambda};\mathbf{p}) = \frac{1}{2}(\mathbf{U}-\mathbf{V})^T\mathbb{K}(\mathbf{p})(\mathbf{U}-\mathbf{V}) + \frac{\alpha}{2}(\Pi\mathbf{U}-\mathbf{U}_{obs})^T\mathbb{G}_{obs}(\Pi\mathbf{U}-\mathbf{U}_{obs}) - \boldsymbol{\Lambda}^T(\mathbb{K}(\mathbf{p})\mathbf{V}-\mathbf{F})$

(saddle point)

⟶ $\begin{bmatrix} \alpha\Pi^T\mathbb{G}_{obs}\Pi & -\mathbb{K} \\ \mathbb{K} & \mathbb{K} \end{bmatrix} \begin{pmatrix} \mathbf{U} \\ \boldsymbol{\Lambda} \end{pmatrix} = \begin{pmatrix} \alpha\Pi^T\mathbb{G}_{obs}\mathbf{U}_{obs} \\ \mathbf{F} \end{pmatrix}$ ➡ $(\mathbb{K} + \alpha\Pi^T\mathbb{G}_{obs}\Pi)\mathbf{U} = \mathbf{F} + \alpha\Pi^T\mathbb{G}_{obs}\mathbf{U}_{obs}$

$\mathbf{V} = \mathbf{U} + \boldsymbol{\Lambda}$

data-based model enrichment (**hybrid twin**)

- **Step 2 (correction):** solve $\min_{\mathbf{p}\in\mathcal{P}} \mathcal{F}(\mathbf{p})$ *(hierarchic updating)*

⟶ gradient-based approach with adjoint state method ($\nabla_\mathbf{p}\mathcal{F} = \frac{\partial}{\partial \mathbf{p}}\mathcal{L}(\mathbf{U},\mathbf{V},\boldsymbol{\Lambda};\mathbf{p})$)
(steepest descent, Gauss-Newton, BFGS,…)

- Multi-query context ⟶ use of ROM to compute $\hat{\mathbf{s}}(\mathbf{x},t,\mathbf{p},\alpha,\mathbf{u}_{obs},\dots)$ (POD, LATIN-PGD)

[Bouclier *et al.* 2013, Marchand *et al.* 2016, Bhattacharyya & LC 2026]

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mCRE Framework

■ Nonlinear constitutive laws (generalized standard materials [Halphen & Nguyen 1975])

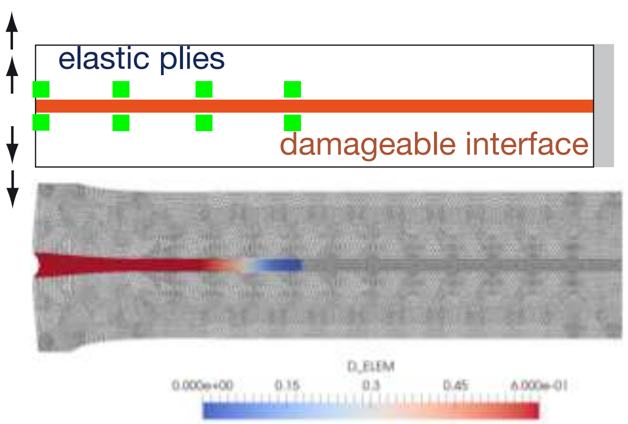
use of 2 dual thermodynamics potentials / CRE measures from Legendre-Fenchel residuals

$$\mathbf{s} = \frac{\partial \psi}{\partial \mathbf{e}_e} \quad ; \quad \mathbf{s} = \frac{\partial \varphi}{\partial \dot{\mathbf{e}}_p}$$

state equations ; evolution laws

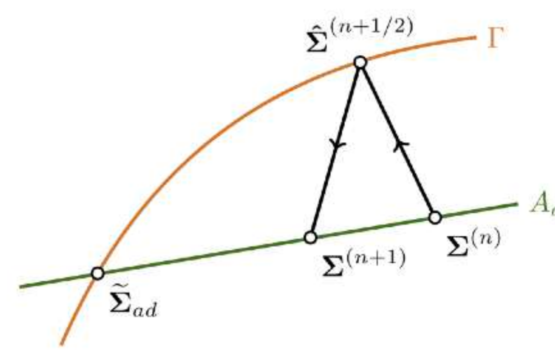
$$\boxed{\mathcal{E}^2_{CRE|t} = \int_\Omega \eta_\psi(\hat{\mathbf{e}}_e, \hat{\mathbf{s}}) + \int_0^t \int_\Omega \eta_\varphi(\dot{\hat{\mathbf{e}}}_p, \hat{\mathbf{s}})}$$

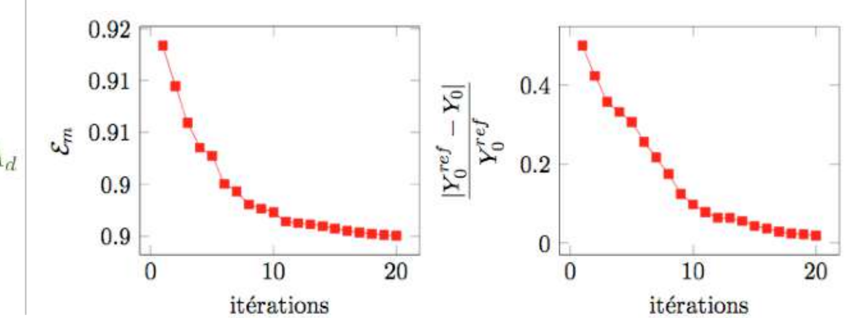
with
$$\left| \begin{array}{l} \eta_\psi(\hat{\mathbf{e}}_e, \hat{\mathbf{s}}) = \psi(\hat{\mathbf{e}}_e) + \psi^*(\hat{\mathbf{s}}) - \hat{\mathbf{s}} \cdot \hat{\mathbf{e}}_e \\ \eta_\varphi(\dot{\hat{\mathbf{e}}}_p, \hat{\mathbf{s}}) = \varphi(\dot{\hat{\mathbf{e}}}_p) + \varphi^*(\hat{\mathbf{s}}) - \hat{\mathbf{s}} \cdot \dot{\hat{\mathbf{e}}}_p \end{array} \right.$$



$$\dot{d} = \frac{k}{a}\left(1 - exp\left[-a\left\langle \frac{Y - Y_0}{Y_c - Y_0} - d^2 \right\rangle_+\right]\right)$$

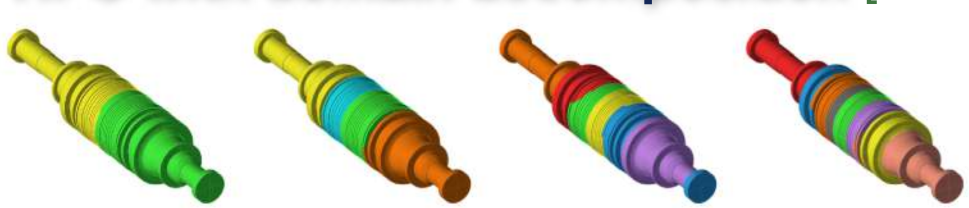
[Marchand et al. 19]

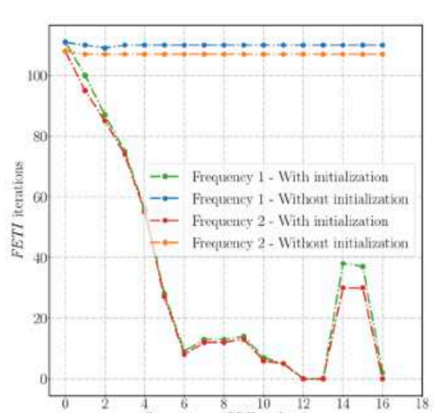


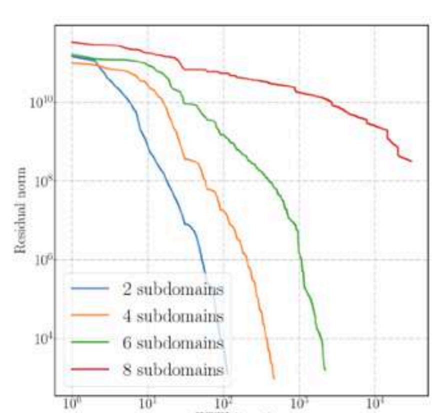


■ Some recent implementations

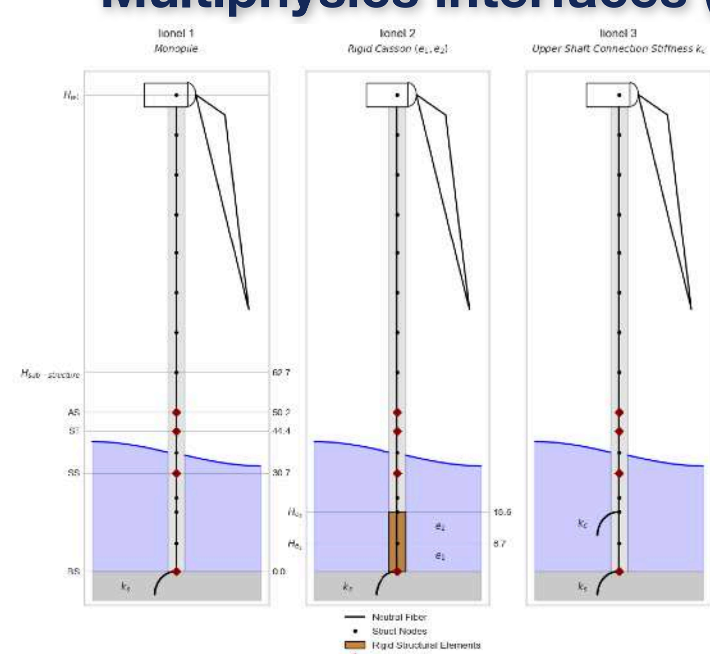
HPC with domain decomposition [Samir *et al.* 2023]

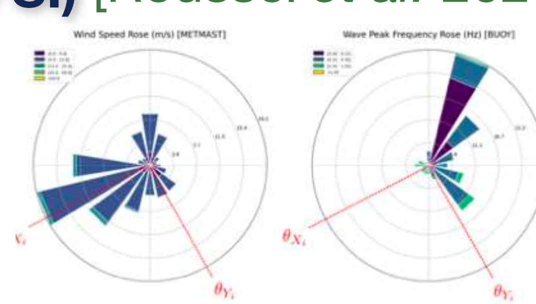


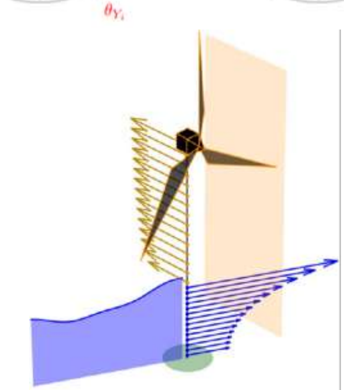




Multiphysics interfaces (FSI) [Roussel *et al.* 2023]



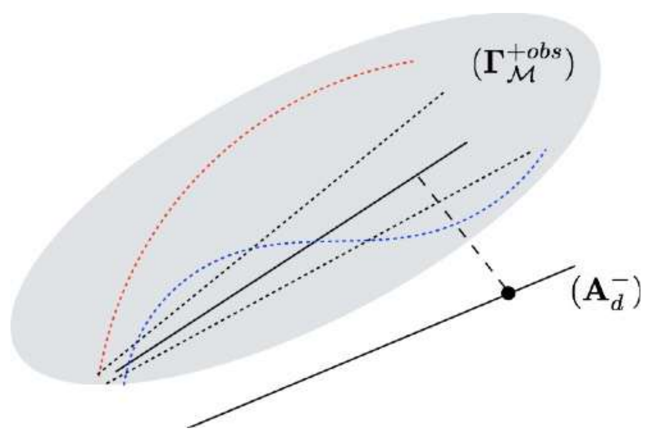


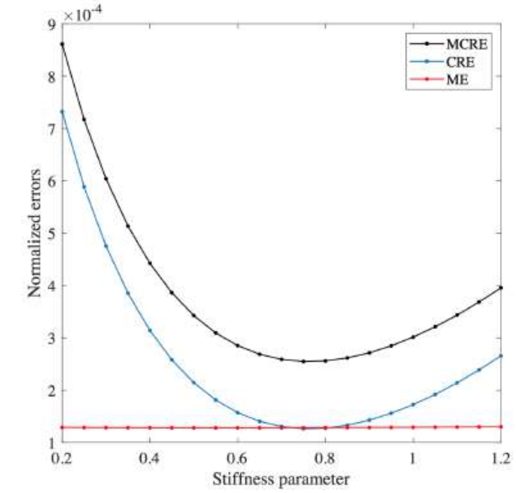


mCRE Framework

■ Data-based model selection [Nguyen *et al.* 2022, Nguyen & LC 2024]

GOAL: select a reference model which is **consistent with the richness of observations**

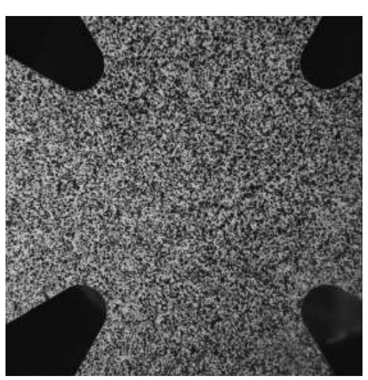


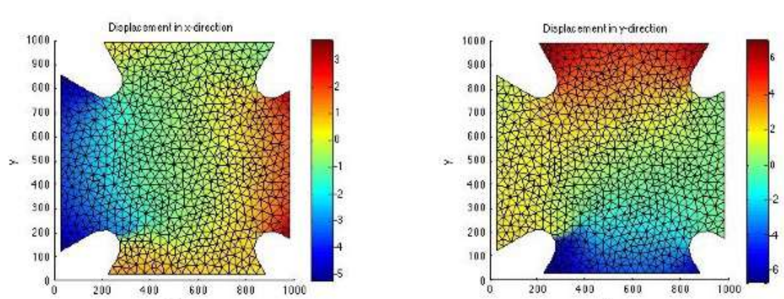


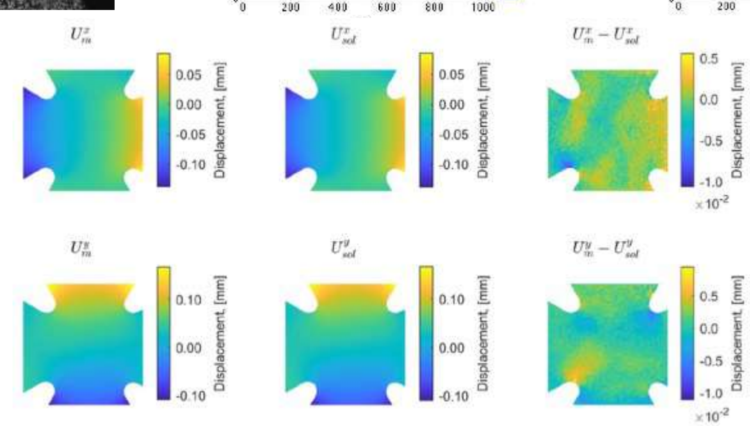
<u>mIDIC (integrated version):</u>

$$\mathcal{E}^2_{mIDIC}(\hat{\mathbf{U}},\hat{\mathbf{V}},\mathbf{p}) = \frac{1}{2}(\hat{\mathbf{U}}-\hat{\mathbf{V}})^T\mathbb{K}(\mathbf{p})(\hat{\mathbf{U}}-\hat{\mathbf{V}}) + \frac{\alpha}{2}.\frac{1}{2\gamma_f^2 N_{pix}}\sum_{\mathbf{x}\in ROI}\Big(f(\mathbf{x}) - g(\mathbf{x}+\mathbb{N}(\mathbf{x})\hat{\mathbf{U}})\Big)^2$$

CRE term (modeling error) *correlation residual (gray level conservation)*





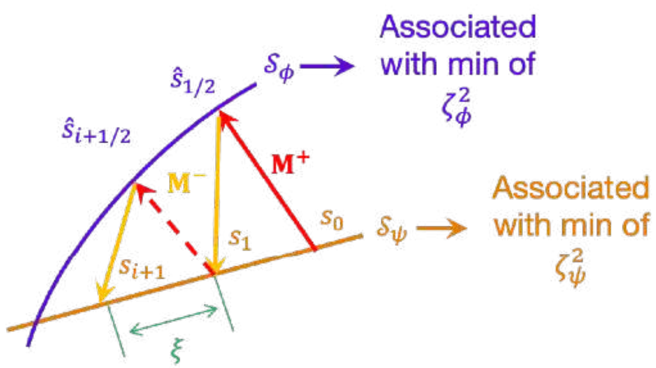


MODEL	$\overline{E}^2_{CRE}$
Initial isotropic elasticity	17.56
Orthotropic elasticity	3.27
Elasto-plasticity (Prandtl-Reuss)	2.29
Adapted mesh	1.38

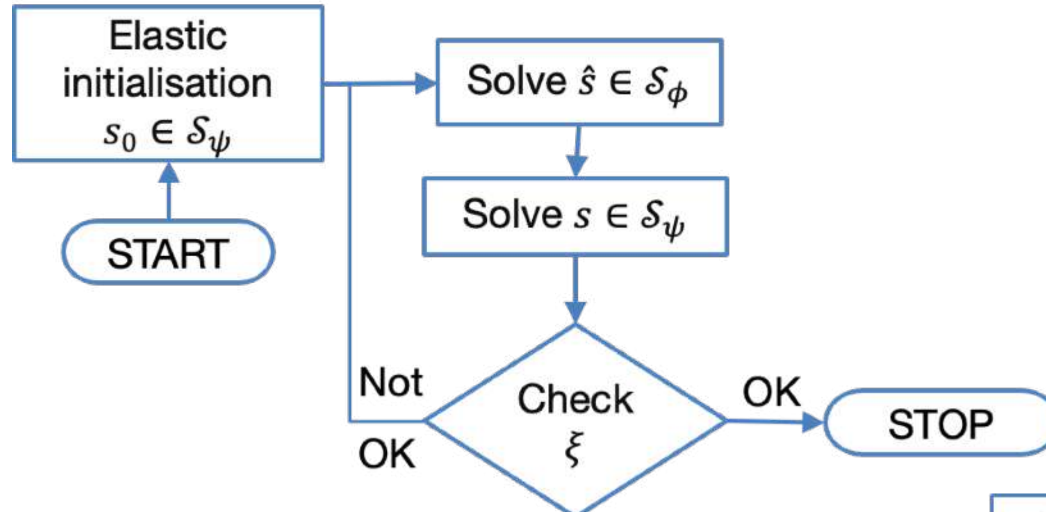
Reduced Order Modeling

[Bhattacharyya & LC 2026]

■ LATIN-PGD type approach



$s = \{\boldsymbol{\varepsilon}_u, \boldsymbol{\varepsilon}_v\}$ $\quad$ $\hat{s} = \{\boldsymbol{\sigma}_u, \boldsymbol{\sigma}_v, \boldsymbol{\varepsilon}_u^p, \boldsymbol{\varepsilon}_v^p, \boldsymbol{X}_u, \boldsymbol{X}_v, \boldsymbol{Y}_u, \boldsymbol{Y}_v\}$



- Corrective terms
  - $\Delta \underline{v}_{i+1} = \underline{v}_{i+1} - \underline{v}_i$
  - $\Delta \underline{u}_{i+1} = \underline{u}_{i+1} - \underline{u}_i$
  - $\Delta \underline{\lambda}_{i+1} = \underline{\lambda}_{i+1} - \underline{\lambda}_i$
  - $\Delta \boldsymbol{\varepsilon}_{u,i+1} = \boldsymbol{\varepsilon}_{u,i+1} - \boldsymbol{\varepsilon}_{u,i}$
  - $\Delta \boldsymbol{\varepsilon}_{v,i+1} = \boldsymbol{\varepsilon}_{v,i+1} - \boldsymbol{\varepsilon}_{v,i}$
  - $\Delta \boldsymbol{\varepsilon}_{\lambda,i+1} = \boldsymbol{\varepsilon}_{\lambda,i+1} - \boldsymbol{\varepsilon}_{\lambda,i}$

- Low-dimensional approximation of full high-dimensional systems
  - $\underline{u}_i(\underline{x},t) = \underline{u}_0 + \sum_{j=1}^{m_u} \alpha_j^u(t)\underline{U}_j(\underline{x})\,,\, \underline{\lambda}_i(\underline{x},t) = \underline{\lambda}_0 + \sum_{j=1}^{m_\lambda} \alpha_j^\lambda(t)\underline{\Lambda}_j(\underline{x})$

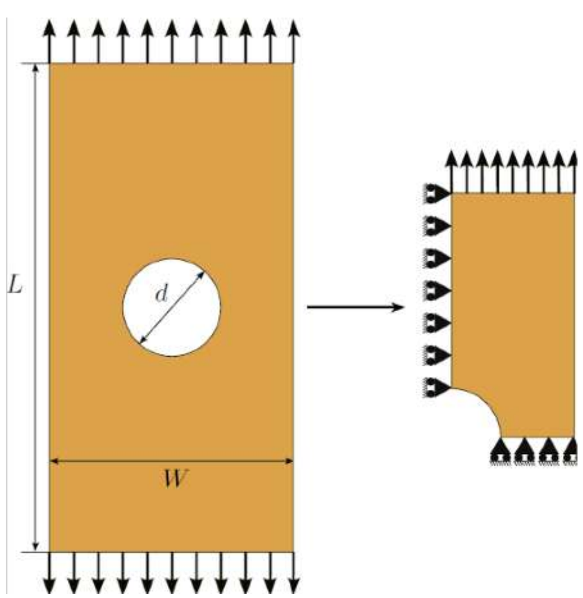
- Update of ROB
  - Variable separation

$$\Delta \underline{u}_{i+1} = \sum_{j=1}^{m_u} \Delta\alpha_j^u(t)\underline{U}_j(\underline{x})$$

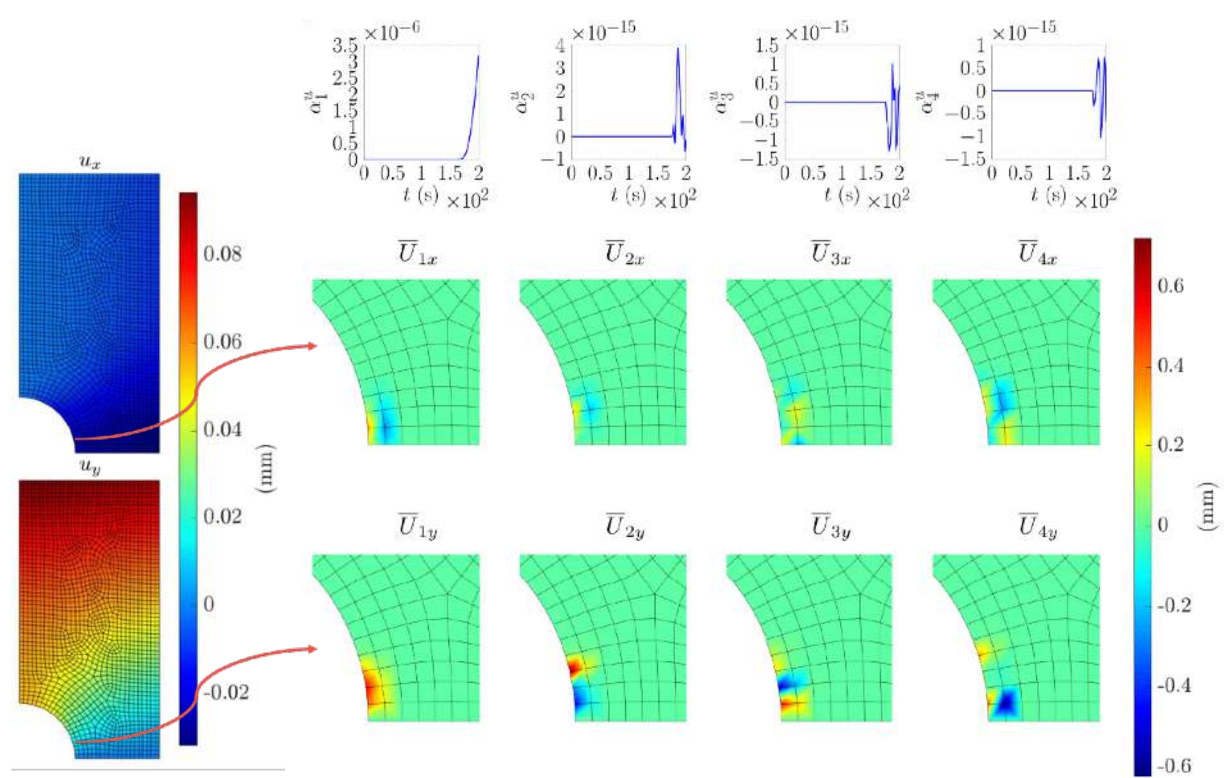
$$\Delta \underline{\lambda}_{i+1} = \sum_{j=1}^{m_\lambda} \Delta\alpha_j^\lambda(t)\underline{\Lambda}_j(\underline{x})$$

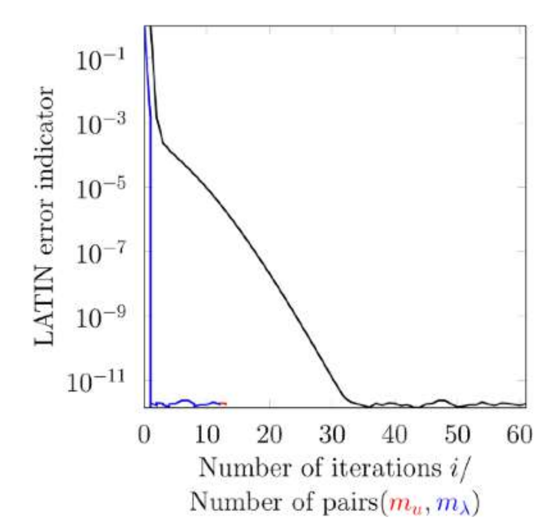
  - Time functions

$$\{\Delta\alpha_j^u\}_{j=1}^{m_u}, \{\Delta\alpha_j^\lambda\}_{j=1}^{m_\lambda} = \underset{\{\Delta\alpha_j^u\}_{j=1}^{m_u}, \{\Delta\alpha_j^\lambda\}_{j=1}^{m_\lambda}}{\arg\min} \mathcal{L}$$



- State laws
  - $\boldsymbol{\sigma} = \mathbf{C}(E,\nu) : \boldsymbol{\varepsilon}^e$
  - $R = R_\infty p$
- Evolution laws
  - $\dot{\boldsymbol{\varepsilon}}^p = \left\langle \frac{f^p}{K} \right\rangle^n \left[\frac{3}{2} \frac{\boldsymbol{\sigma}^D}{\sqrt{\frac{3}{2}\boldsymbol{\sigma}^D : \boldsymbol{\sigma}^D}} \right]$
  - $\dot{p} = \left\langle \frac{f^p}{K} \right\rangle^n$





Error estimate available
[Chamoin *et al.* 2017]

Outline

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- **mCRE framework for data assimilation**
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  Application to the online control of shaking table tests on large-scale damageable concrete buildings
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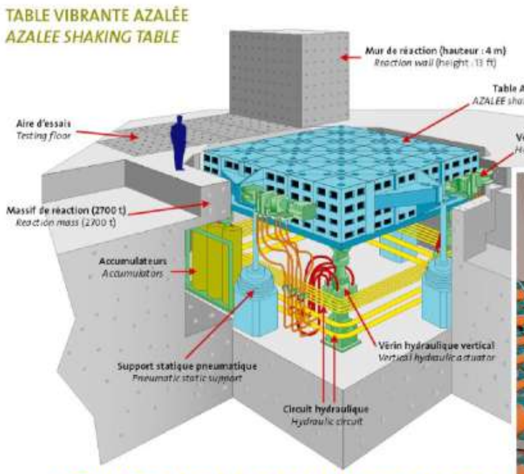
LMPS

Application: SHM on Concrete Buildings

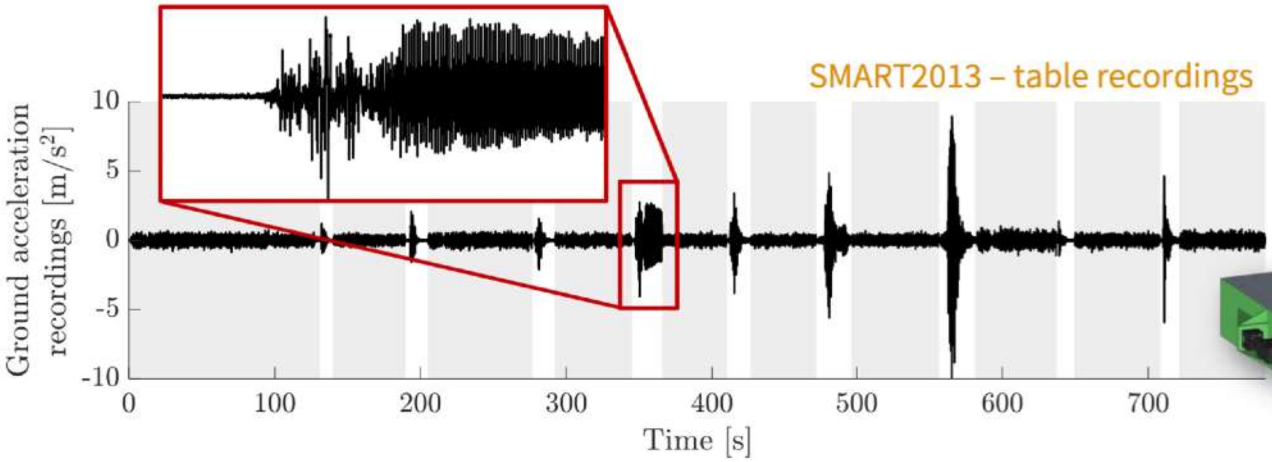
- **Automated control of dynamics shaking-table tests**

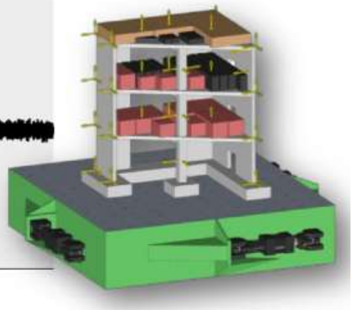
  - low-frequency dynamics (earthquake engineering)
  - SMART 2013 benchmark (CEA/EDF)
  - sequence of gradually damaging tests on a concrete structure
  - command on hydraulic actuators
  - if inappropriate control, unstable experiment



AZALEE shaking table and one of its hydraulic actuator

SMART2013 – table recordings





→ modal signature is the key input feature for linear control

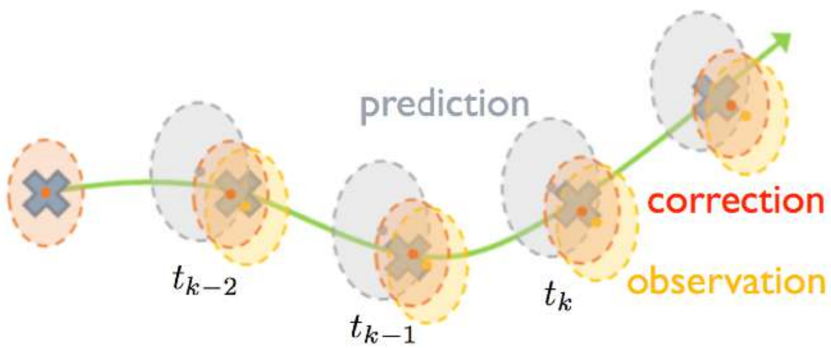
→ on-the-fly assimilation to monitor frequency drop (due to damage)

Sequential Version of mCRE

Kalman Filtering

Dynamical system (linear):

$$x_k = M_k x_{k-1} + B_k u_k + w_k \quad \text{(model for state evolution)}$$
$$y_k = H_k x_k + v_k \quad \text{(observations)}$$



recursive state estimate [Kalman 1960]
(MAP for Gaussian PDFs)

Prediction

$$\hat{x}_{k|k-1} = M_k \hat{x}_{k-1|k-1} + B_k u_k \quad \text{(mean)}$$
$$P_{k|k-1} = M_k P_{k-1|k-1} M_k^T + Q_k \quad \text{(covariance)}$$

$Q_k \rightarrow \mathrm{E}[w_k w_k^T]$

Correction

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (y_k - H_k \hat{x}_{k|k-1})$$
$$P_{k|k} = (I - K_k H_k) P_{k|k-1}$$

$$\boxed{\begin{aligned} K_k &= P_{k|k-1} H_k^T S_k^{-1} \quad \text{(Kalman gain: weights innovation)} \\ S_k &= H_k P_{k|k-1} H_k^T + R_k \end{aligned}}$$

$R_k \rightarrow \mathrm{E}[v_k v_k^T]$

Sequential Version of mCRE

Extension to nonlinear dynamical systems

$$x_k = M(x_{k-1}, u_k) + w_k$$
$$y_k = H(x_k) + v_k$$

→ extended KF (EKF)
unscented KF (UKF) [Julier & Uhlmann 1997]
...

- deterministic selection of σ-points (Cholesky decomposition of cov. matrix)
- transformation of these points $\{x_i\}_{i=1,\dots,2N+1}$ through nonlinear functions (// comput.)
- high accuracy (order 3), but strongly depends on data noise [Li *et al.* 16]

Extension to parameter estimation

$$x_k = M(x_{k-1}, p_k, u_k) + w_k \longrightarrow$$ state + parameter estimation

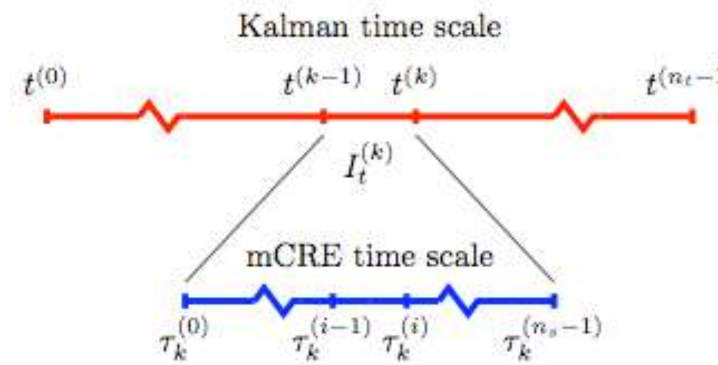
Joint Kalman Filter (KF on extended state)	**Dual Kalman Filter** (combines 2 KFs)
$p_k = p_{k-1} + w_k^p$ (stationarity hyp.) $\tilde{x}_k = [x_k^T, p_k^T]^T$ (concatenation)	$p_k = p_{k-1} + w_k^p$ (parameters as state vect.) $y_k = H_{dual}(x_k, p_k, u_k, w_k) + v_k$ observer = state evaluation operator (based on a second KF, for given p_k)

change of observer metric using mCRE: **MDKF strategy (enhanced robustness to noise)**

$\nabla_p \mathcal{E}_{mCRE}(x_k, p_k, y_k) + v_k = 0$ [Marchand *et al.* 2016, Diaz *et al.* 2022]

Sequential Version of mCRE

- **Modified Dual Kalman Filter (MDKF)** [Marchand *et al.* 16, Diaz *et al.* 2022,2023]



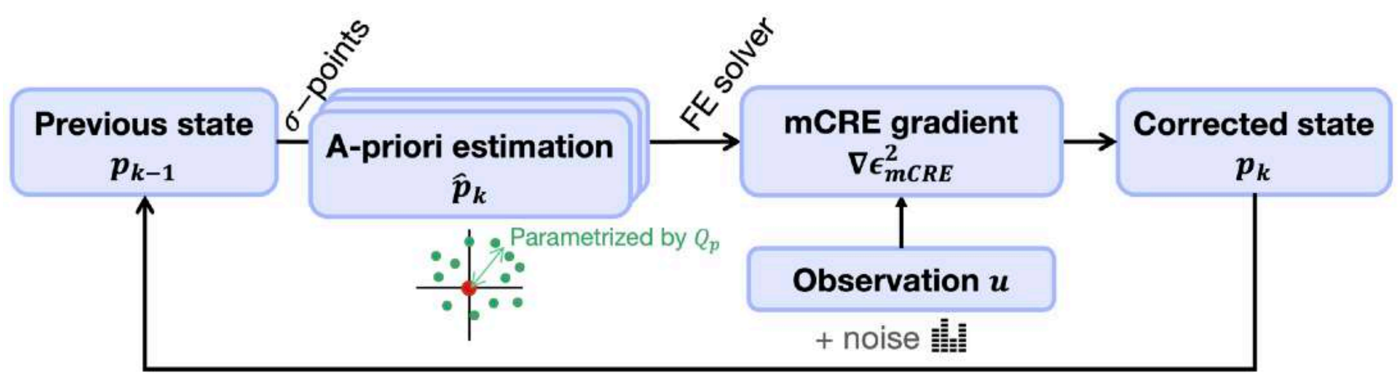
→ **change of observer metric using mCRE in Dual KF**

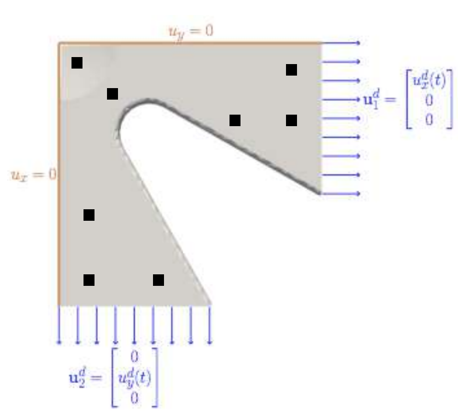
→ considers optimal admissible fields as state estimate

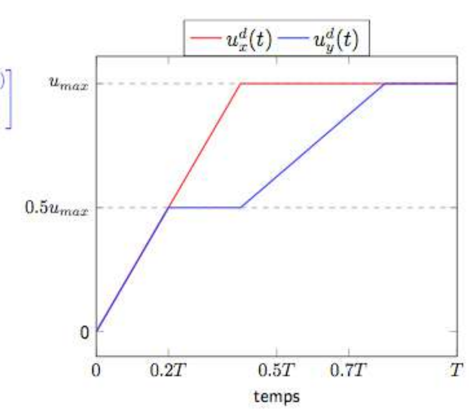
→ automatic calibration of MDKF internal parameters

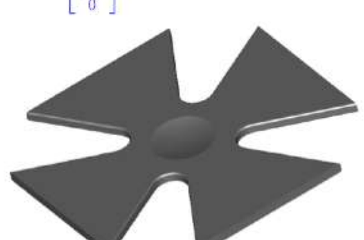
→ enhanced robustness to measurement noise compared to classical UKF

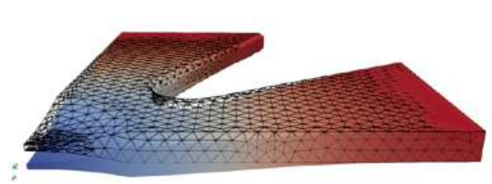
→ use of ROM and other advanced techniques for further numerical efficiency

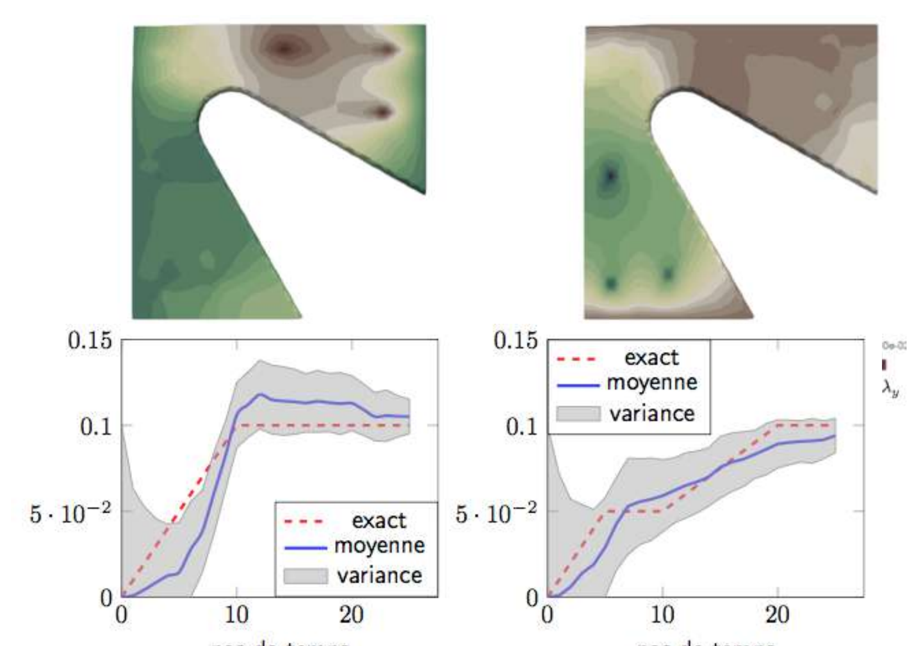












average CPU time
$\approx$
0.2s

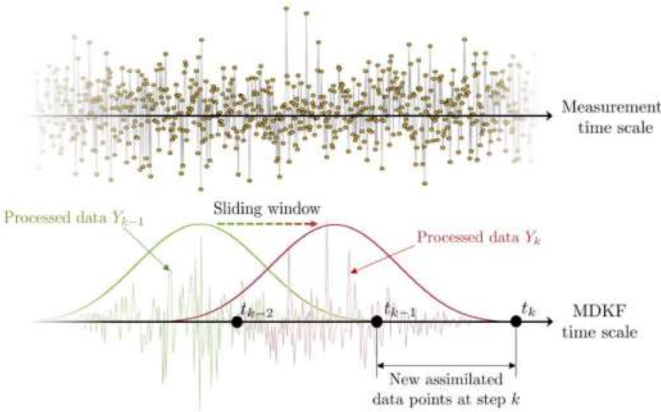
SHM Results

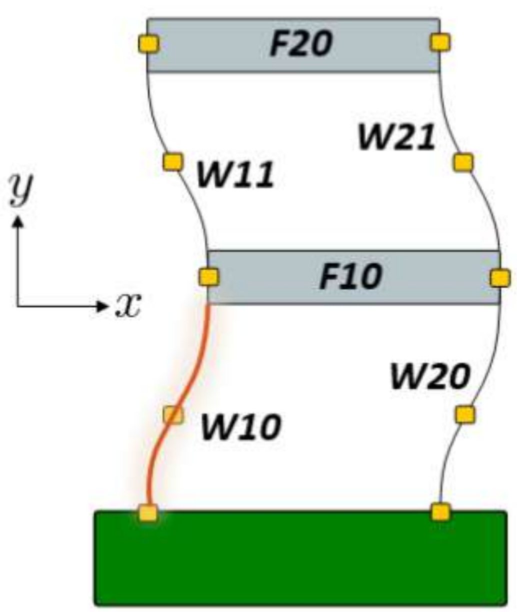
[Diaz *et al.* 2022,2023]

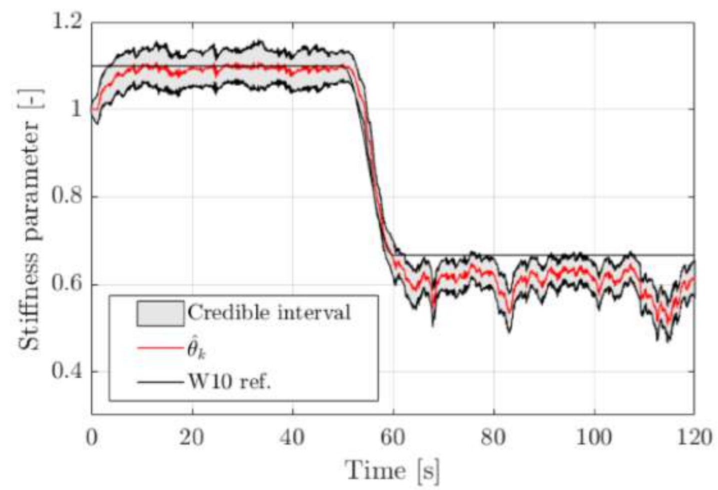
■ Sequential damage assessment in dynamics

<u>mCRE in the frequency domain</u>

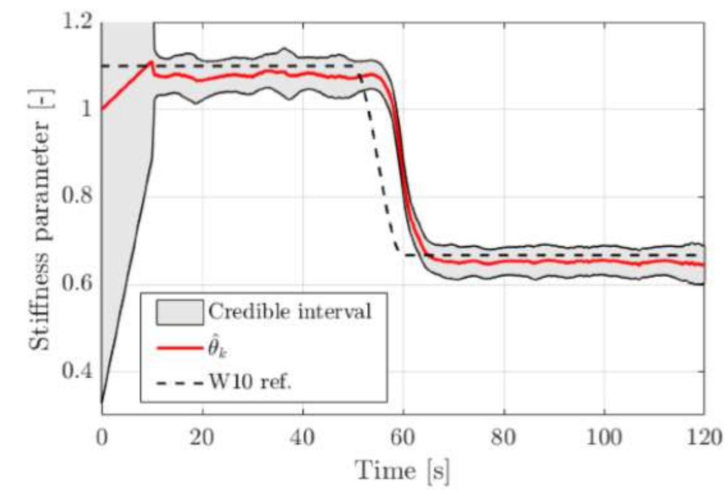
$$e_\omega^2(s,p,Y_\omega) = \zeta_\omega^2(s,p,Y_\omega) + \alpha\|\Pi \circ s - Y_\omega\|_G^2 \Rightarrow J(p) = \int_{D_\omega} z(\omega) e_\omega^2(\hat{s}(p),p,Y_\omega)\,d\omega$$



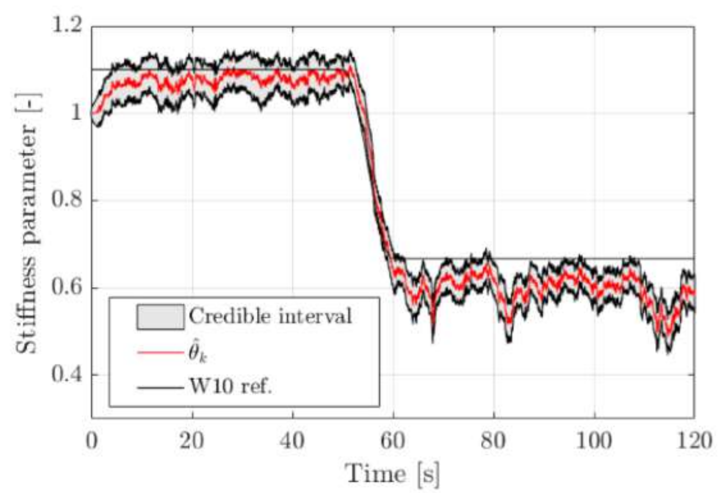




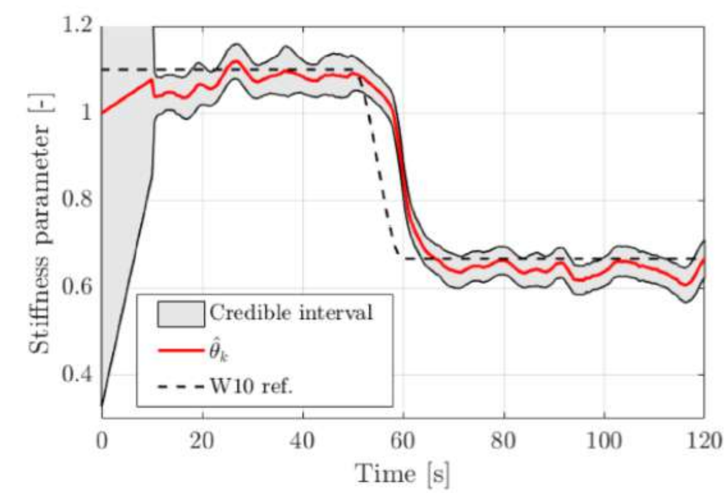
(a) JUKF - $\delta = 0\%, Q_x = 10^{-8}I, Q_\theta = 10^{-7}I, R = 10^{-2}I$



(b) MDKF - $\delta = 0\%, r = 0.5$



(c) JUKF - $\delta = 20\%, Q_x = 10^{-8}I, Q_\theta = 10^{-7}I, R = 10^{-2}I$



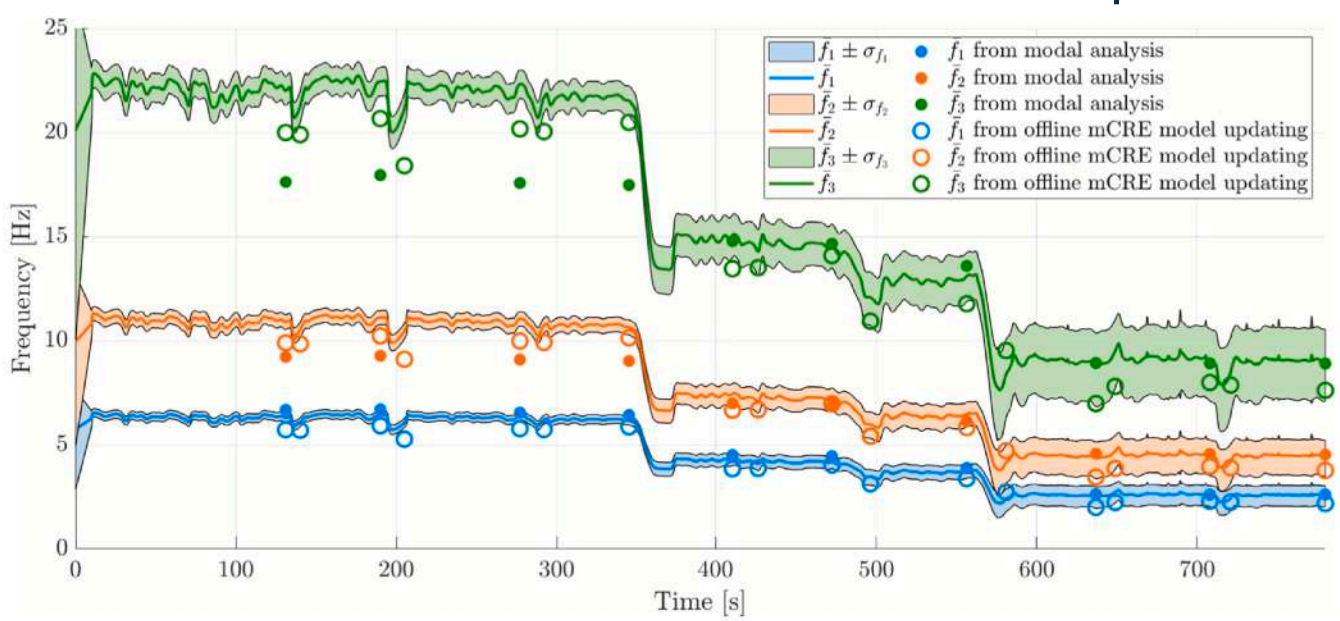
(d) MDKF - $\delta = 20\%, r = 0.001$

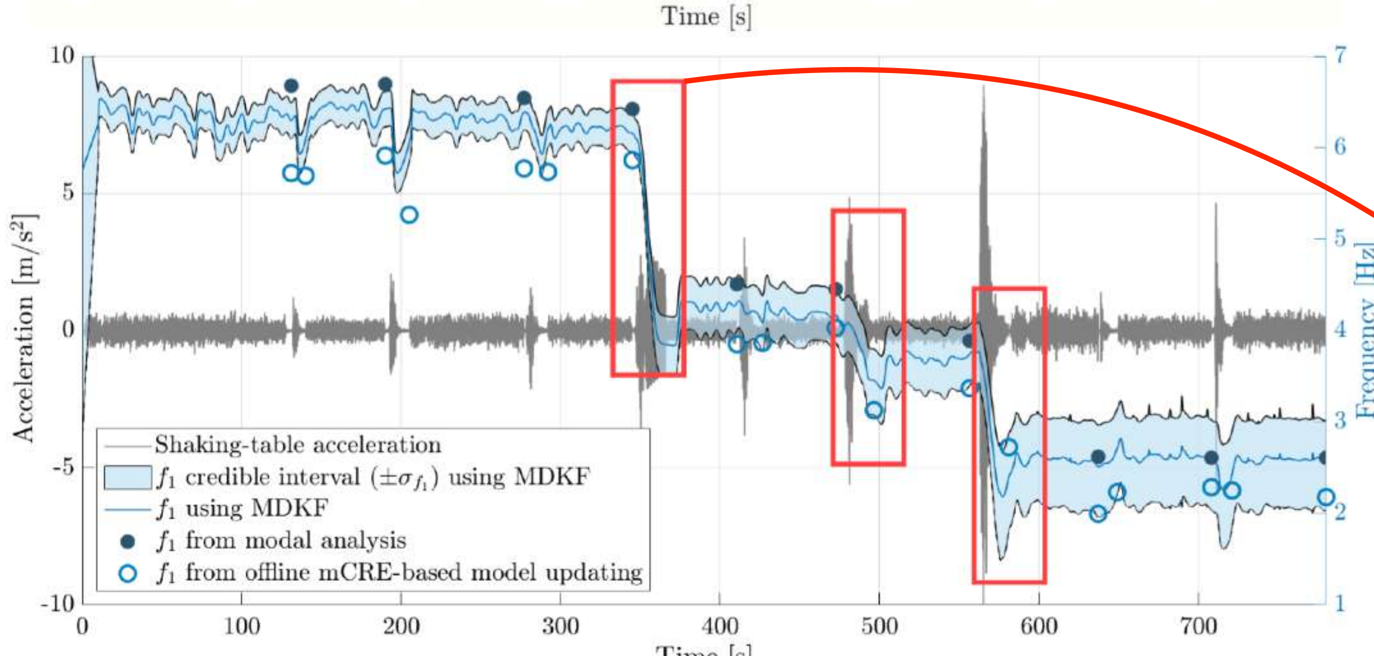
SHM Results

[Diaz *et al.* 2022,2023]

■ Eigenfrequency tracking from sparse & highy noisy measurements

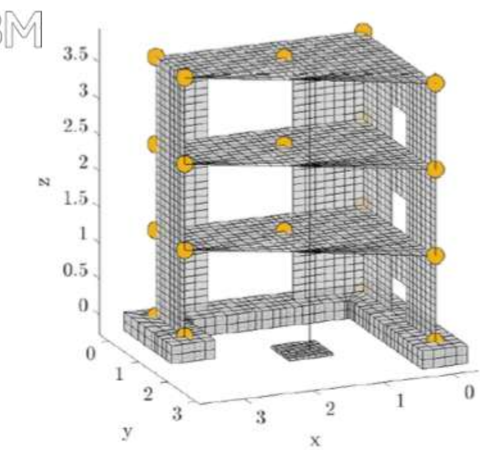
- results obtained with 41 accelerometer recordings from the campaign
- distributed damage parameters on walls & floors
- tracking of the 3 first eigenfrequencies
- real-time constraint successfully achieved | *data window = 0.5 s* / *assimilation < 0.3 s*



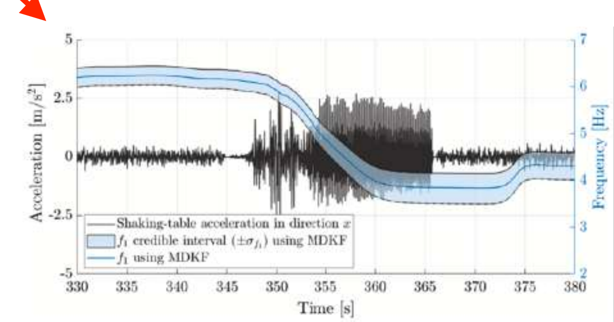


RC specimen of SMART2013 anchored on the AZALEE shaking-table

Cast3M

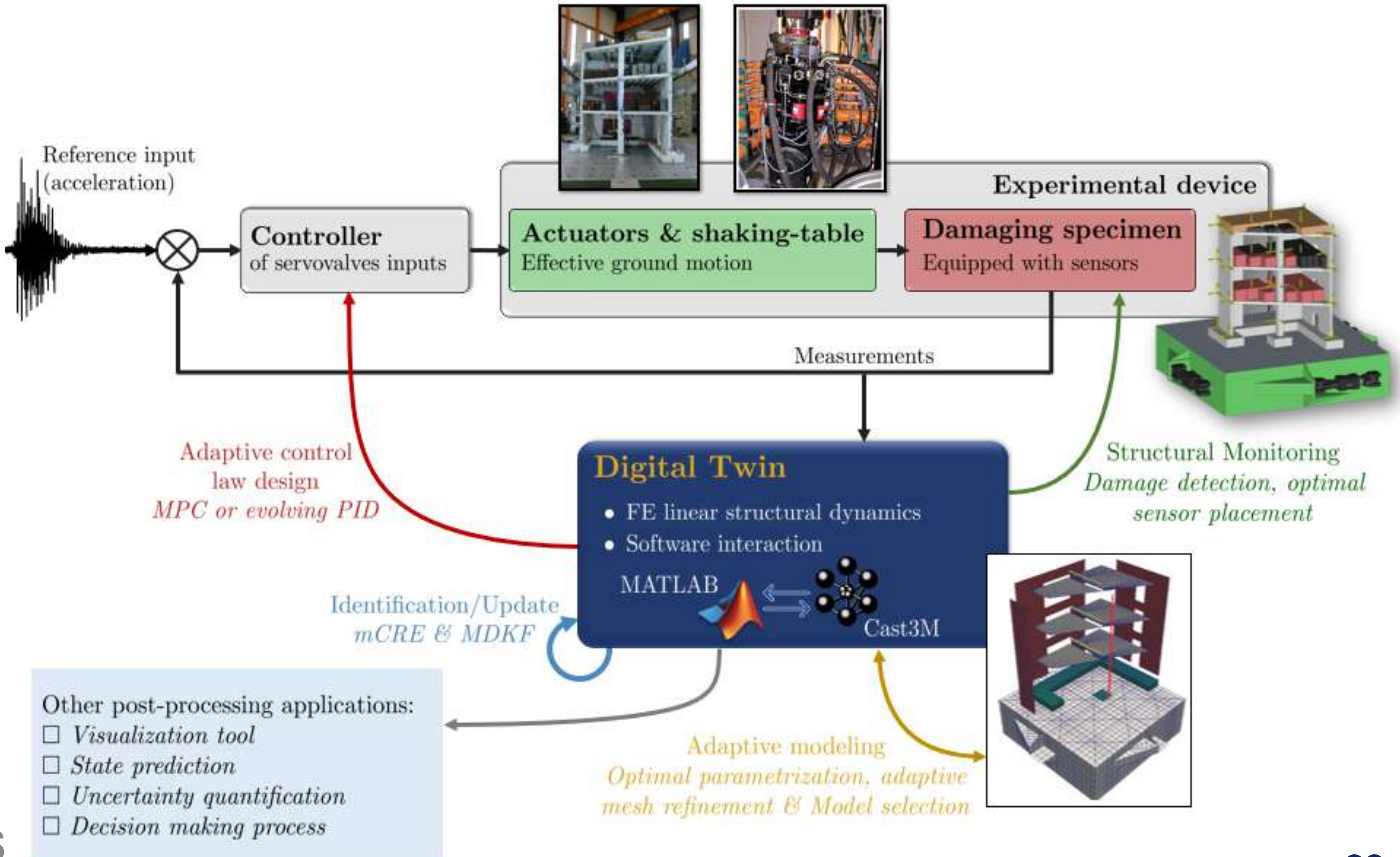


FE model from CEA-EMSI developed in Cast3M



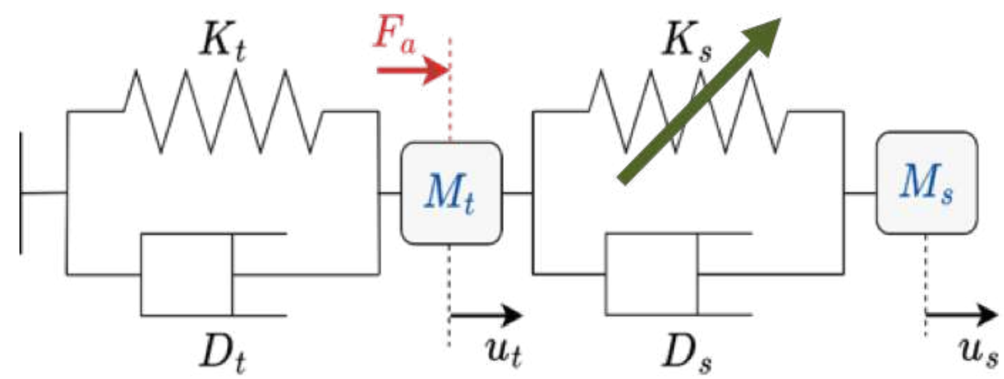
LMPS

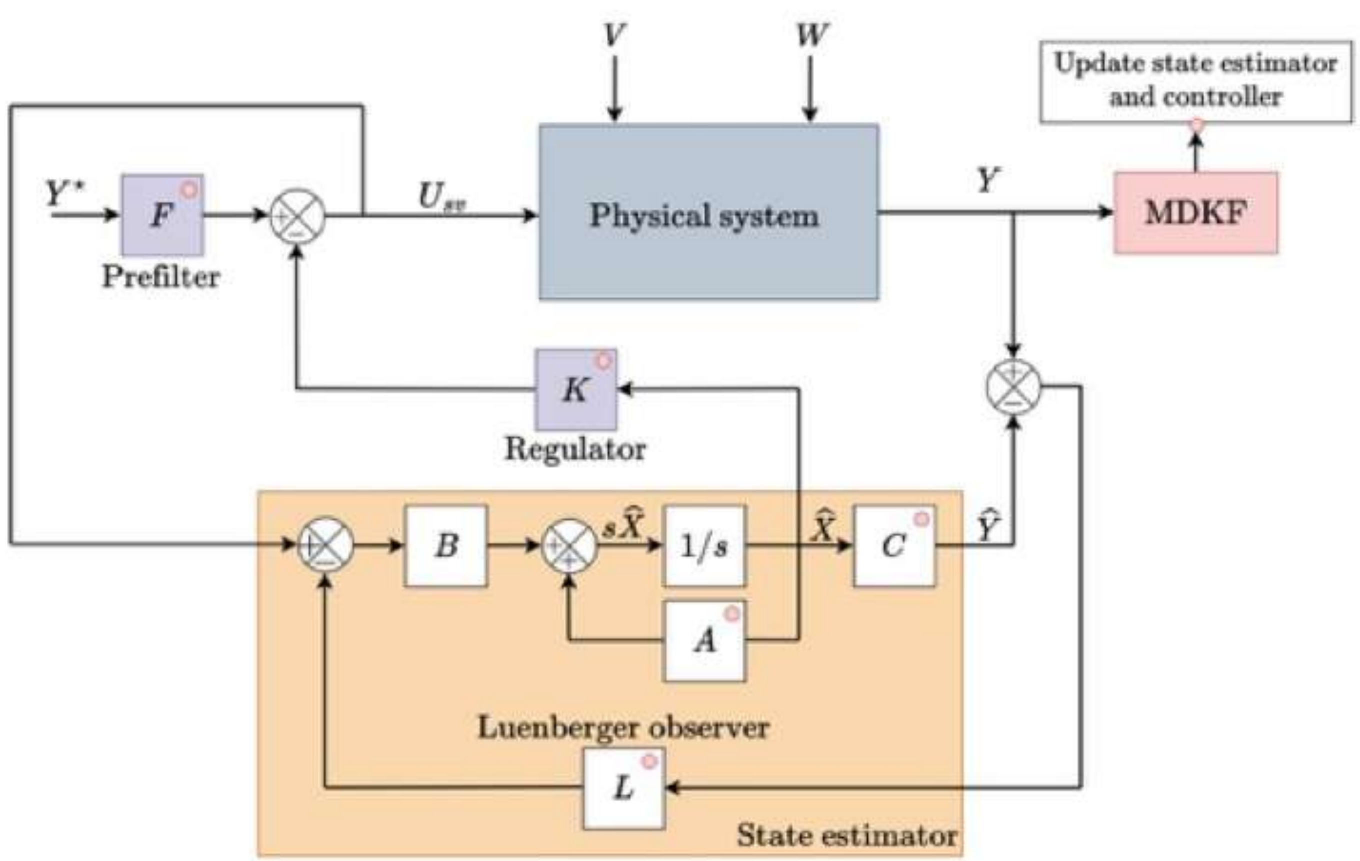
On-the-fly control with adaptive command synthesis

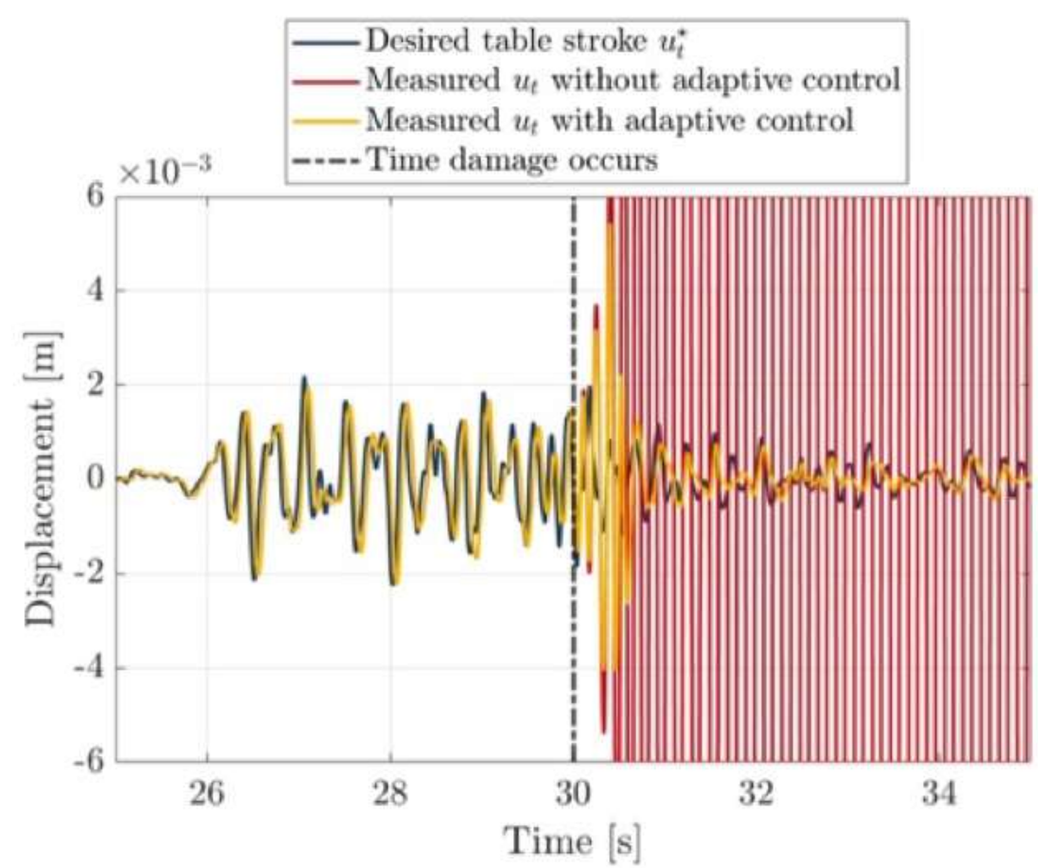


On-the-fly control with adaptive command synthesis

- automatic dynamical drive of hydraulic actuators
- MDKF strategy inserted in a LQP controller







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LMPS

DREAM-ON Project

[ERC-CoG 2021-2026]

https://erc-dreamon.ens-paris-saclay.fr

SMART ENGINEERING STRUCTURES

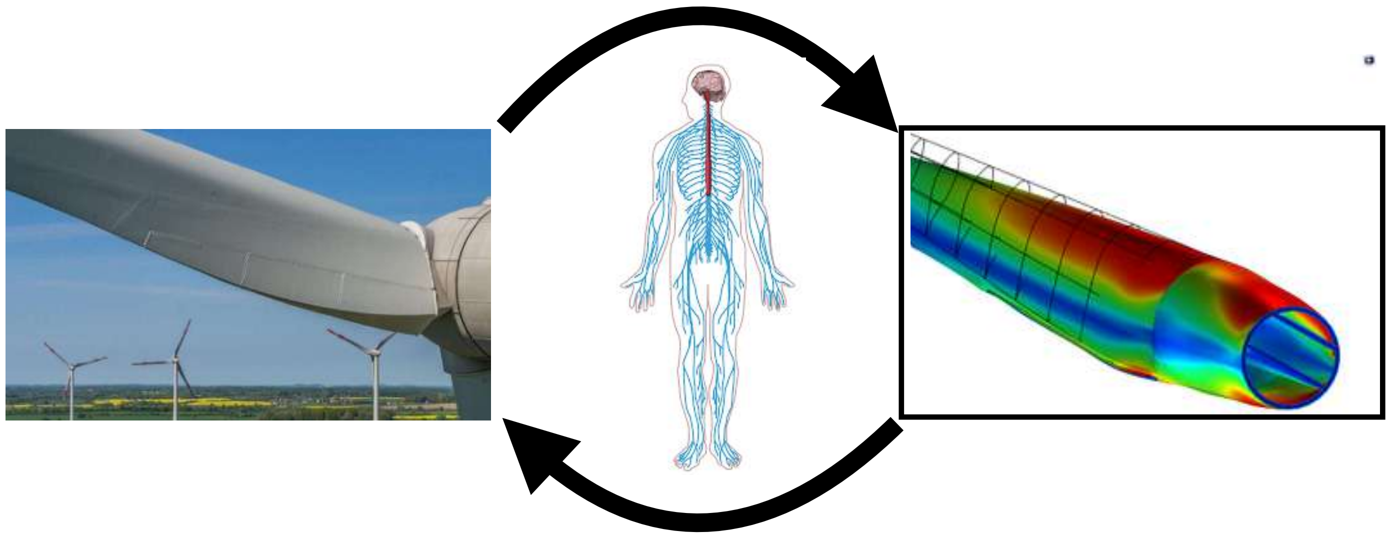
- Integrated simulation-based SHM → online monitoring of structural integrity
- Damage diagnosis, prognosis, and control

Enhanced durability and performance

Anticipated action during service

Optimized maintenance

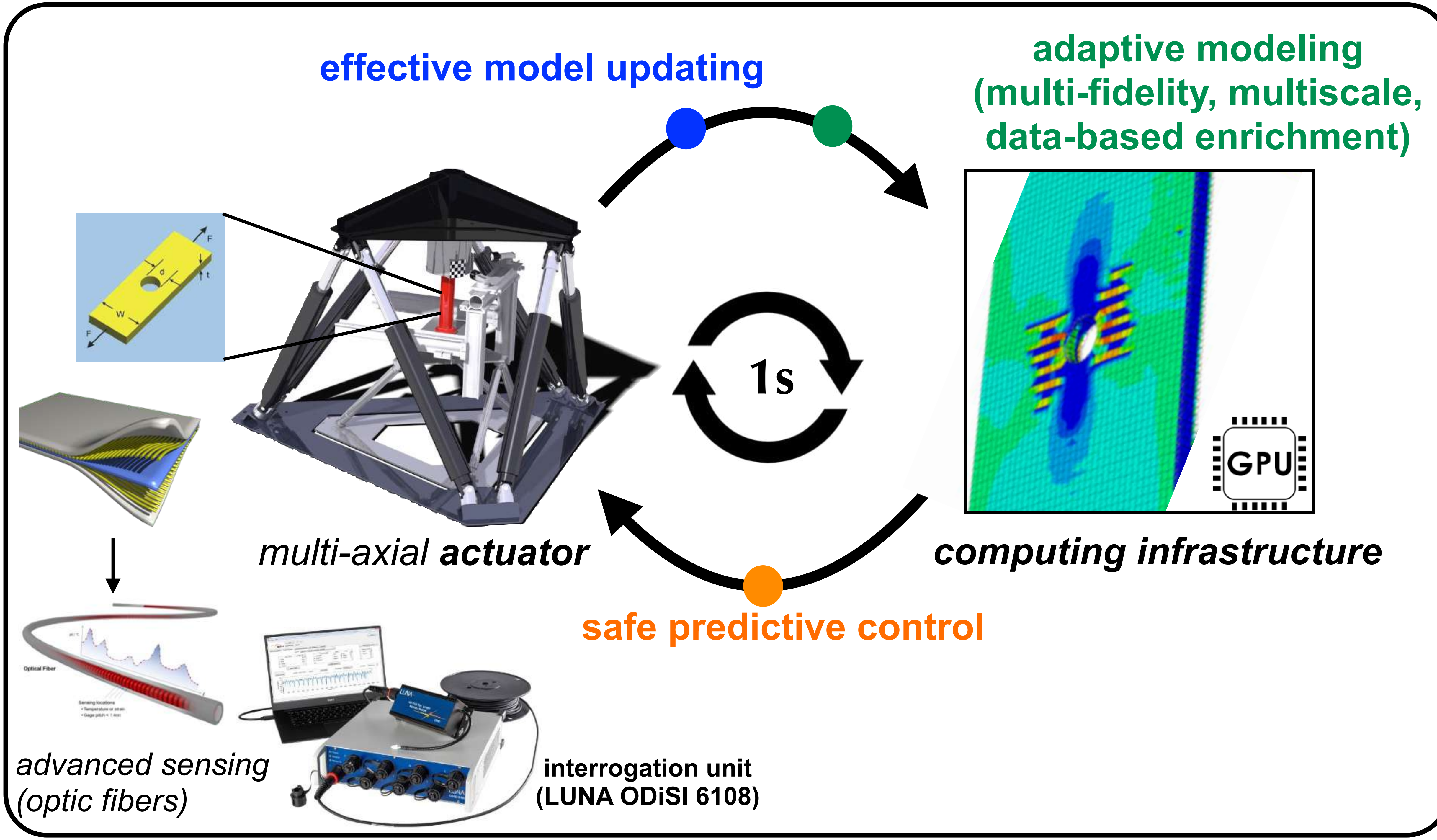
Operation in degraded mode



- Advanced sensing + HF modeling + powerful numerical methods
- Constraints: real-time, portability (edge computing), robustness

DREAM-ON: merging advanced sensing techniques and simulation tools for future SHM technologies, *The Project Repository Journal*, 10:124-127 (2021)

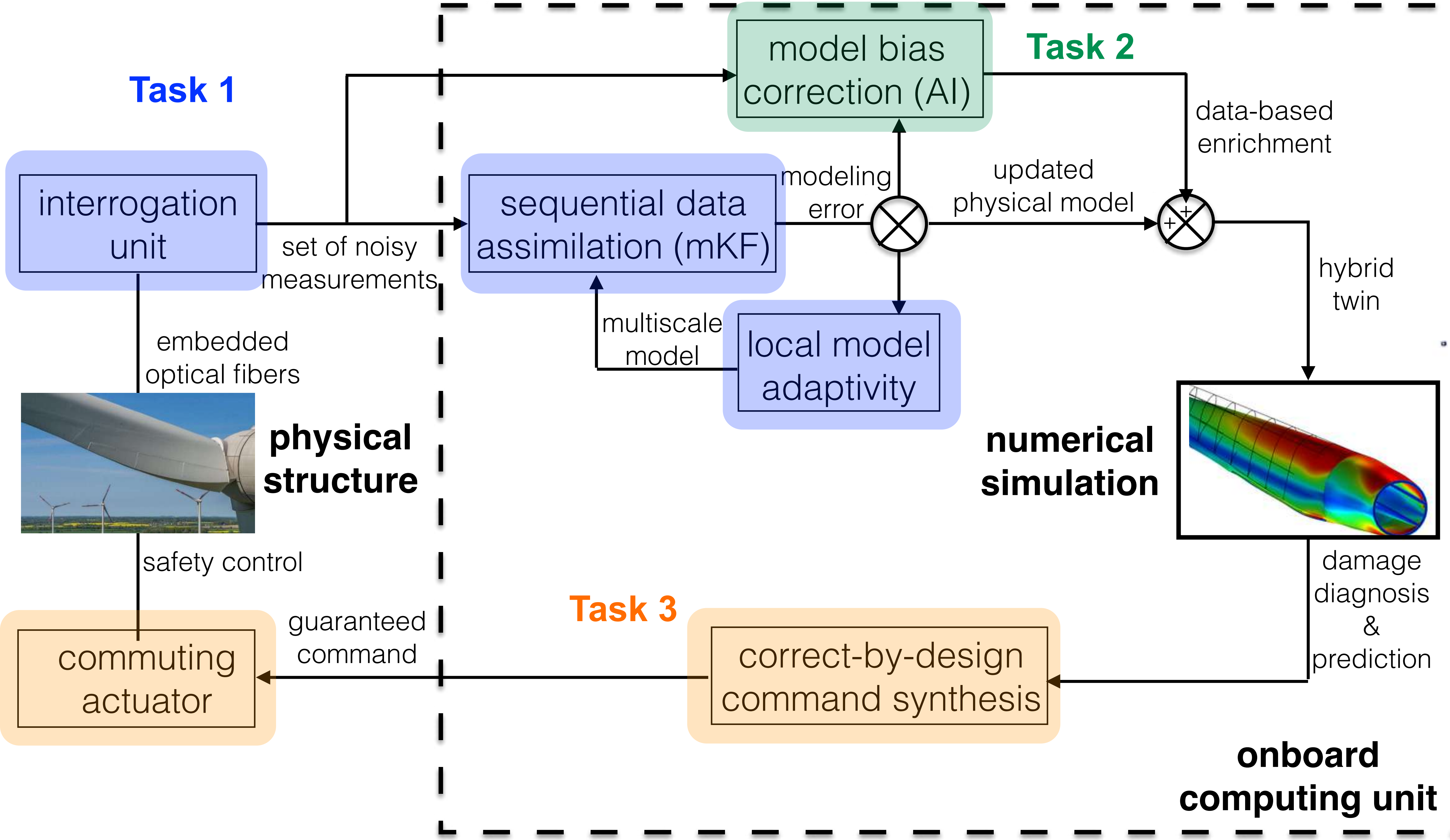
Proof-of-Concept



→ find an optimal loading path given different initial damage conditions

→ make the structure remain in a safety region (operation at performance limits) for various instances of damage

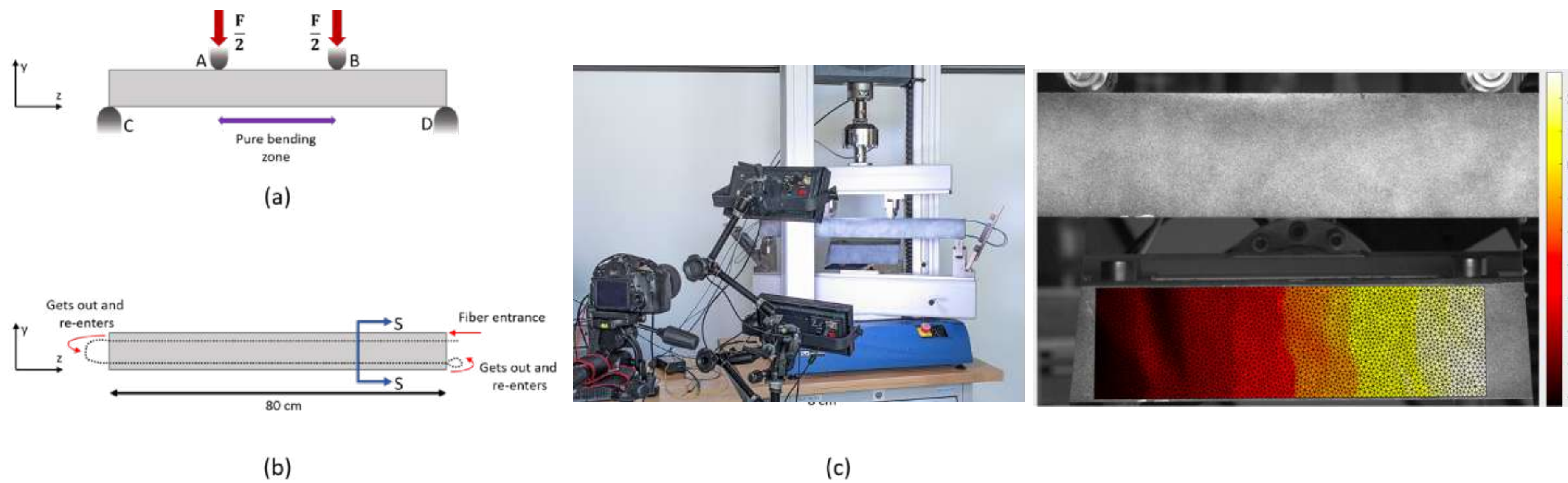
Global Strategy

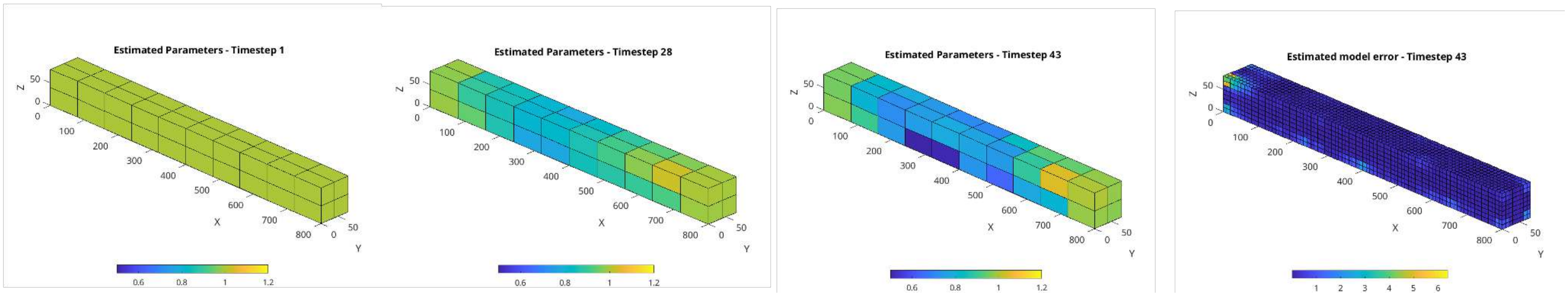


L. C., E. Baranger, A. Benady, P-E. Charbonnel, M. Diaz, S. Farahbakhsh, L. Fribourg, D. Martin-Xavier, M. Poncelet, A novel DDDAS architecture combining advanced sensing and simulation technologies for effective real-time SHM, *Handbook of DDDAS, Springer* (2025)

Task 1: MDKF Strategy with DOFS

- Beam samples under 4-point bending
  - Cement-based mortar reinforced with polyamide and steel fibers
  - Linear, elastic, isotropic and homogeneous material
  - Updated parameter: Damage parameter in zones
  - Dimensions 80 x 8 x 8 cm
  - C3D8 elements (1 x 1 x 1 cm)
- 4 lines of measurements provided by optic fibers
  - Measurement every 2.6 mm





- Application with complex anisotropic damage models (composites, concrete,…)
- Continuous model updating (along the structure life) from data obtained on-the-fly
- Outputs: updated model + mechanical state (optimal admissible fields)

S. Farahbakhsh, M. Poncelet, L.C, Investigation of Distributed Optic Fiber Sensors data loss due to strain gradient, *Experimental Techniques*, online (2025)

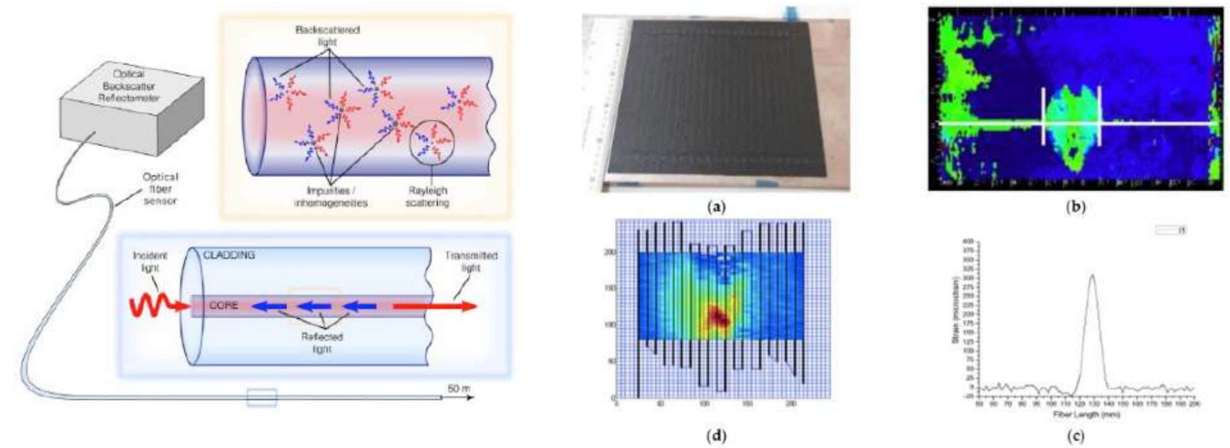
S. Farahbakhsh, L.C., M. Poncelet, Continuous structural health monitoring with a modified dual Kalman filter applied with optic fiber sensing data, *Computers & Structures* (2026)

LMPS

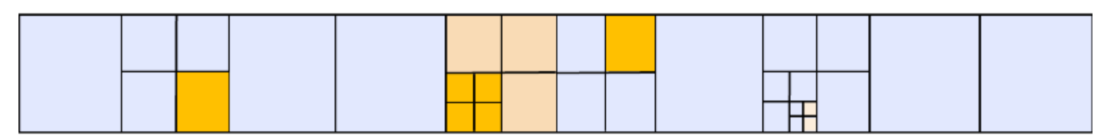
Task 1: MDKF Strategy with DOFS

Numerical optimizations

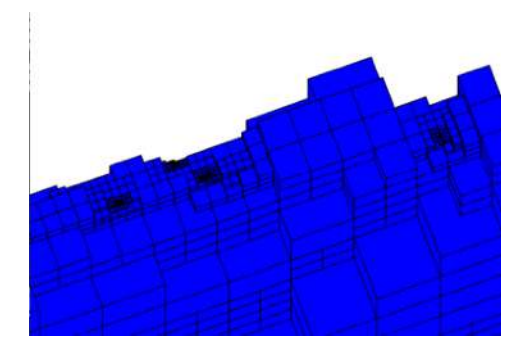
- filtering of DOFS data [Farahbakhsh *et al.* 2025]



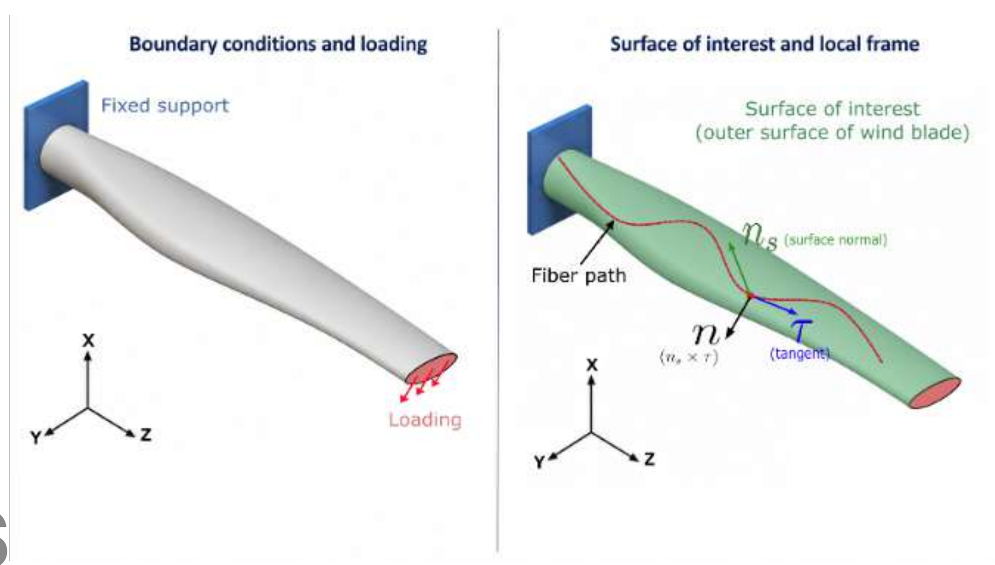
- **sparse regularization**

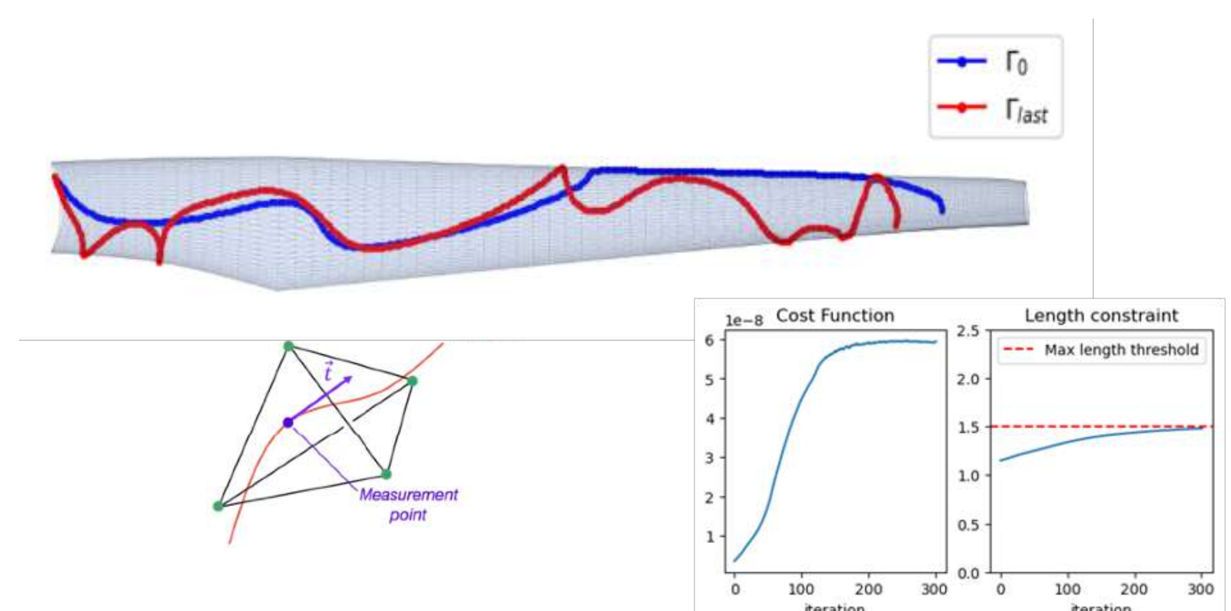


- dynamical **adaptive modeling** in the parameter space (CgFEM)



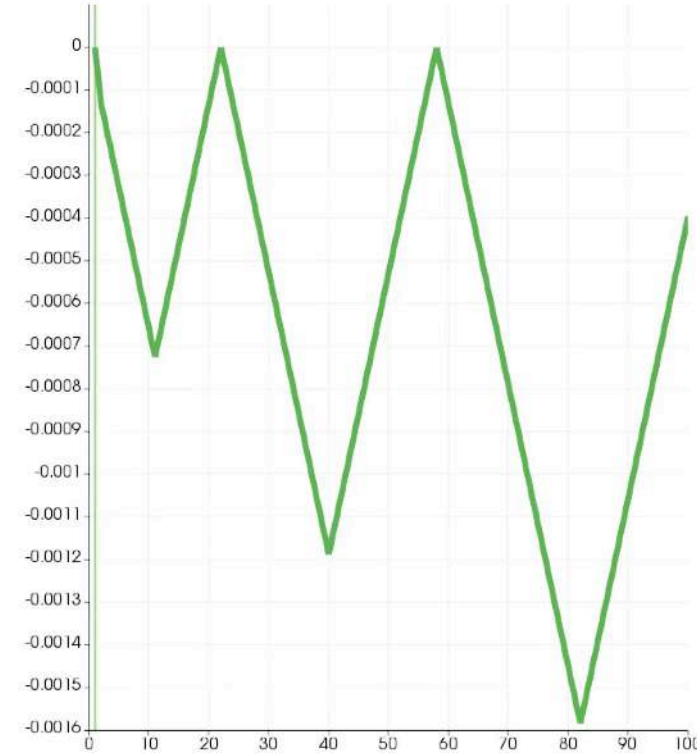
- optimal DOF **sensor placement** [Perez Orozco *et al.* 2025]
  (B-Splines, Fisher information matrix, shape derivative, etc.)

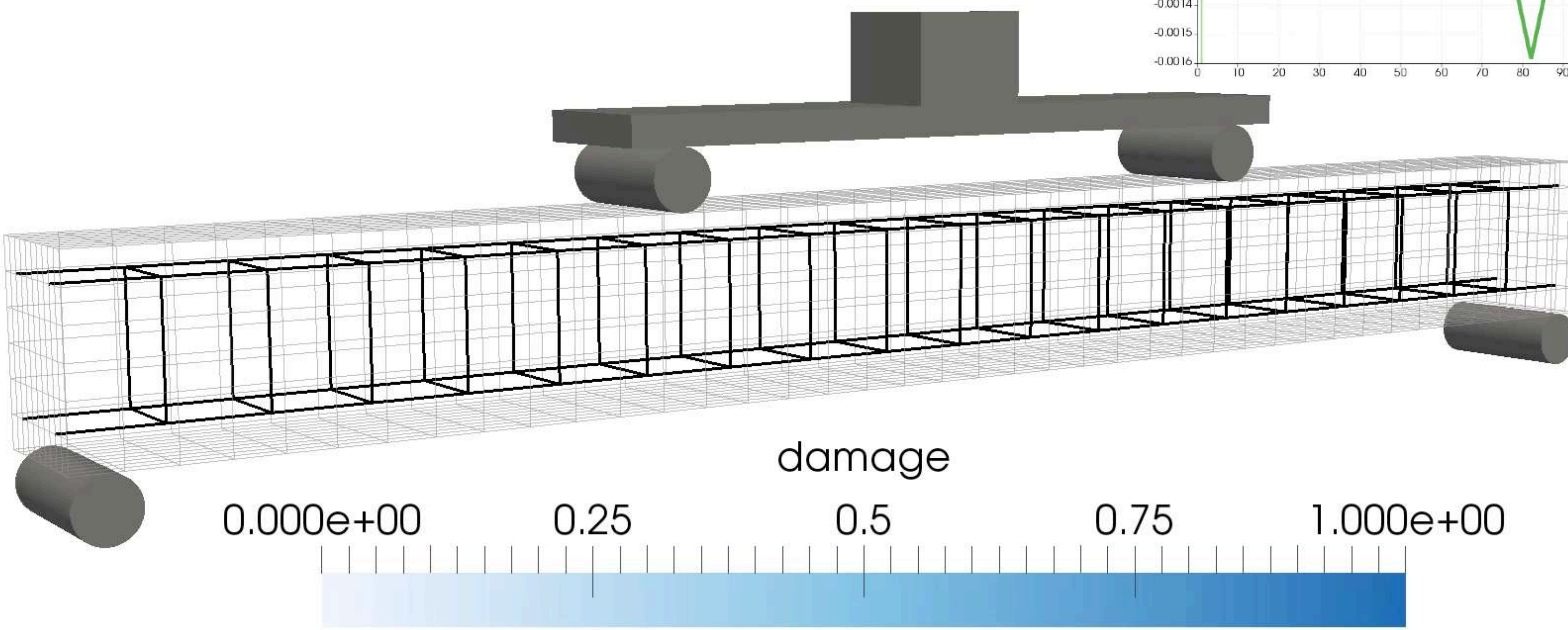


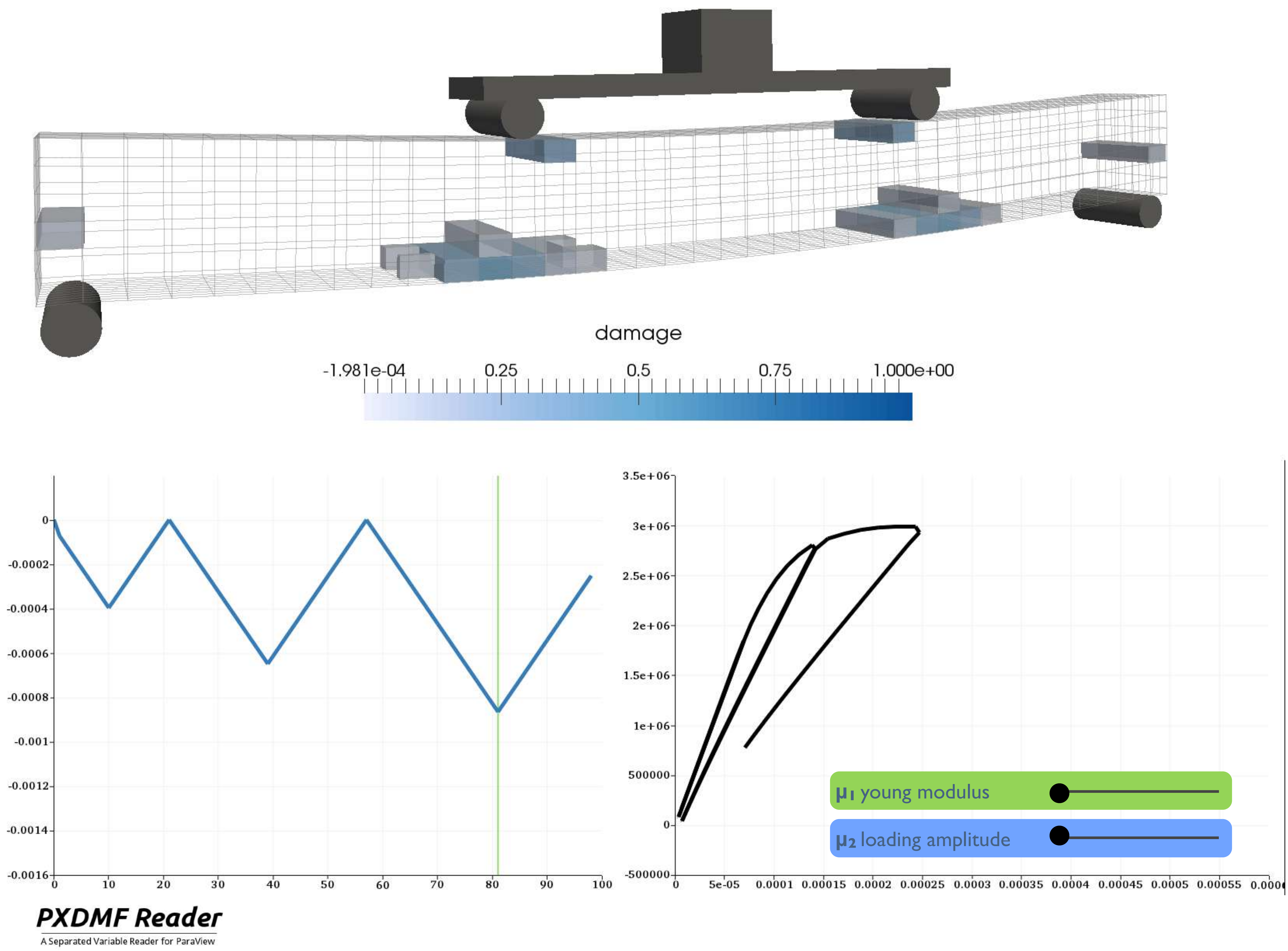


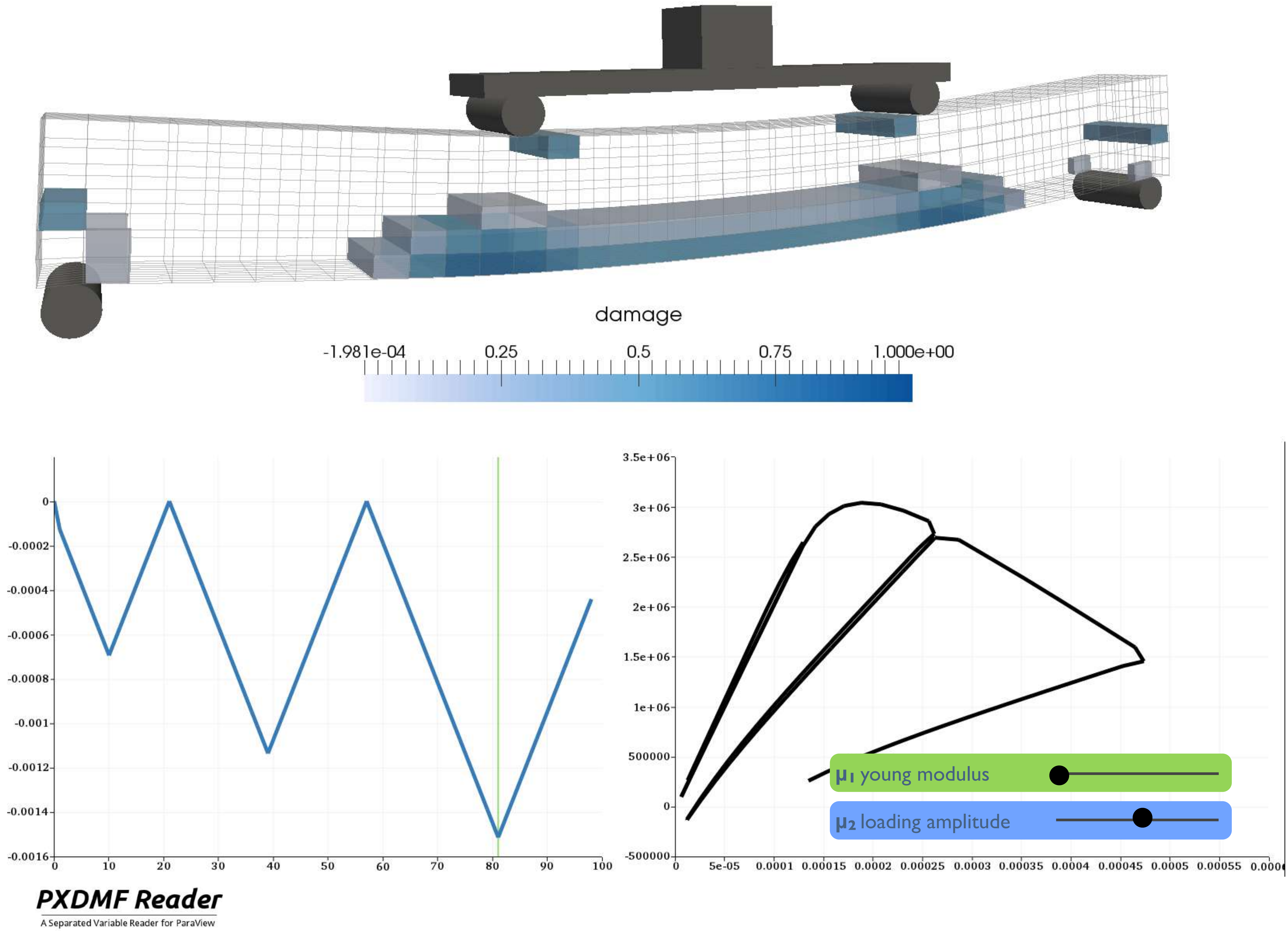
Task 1: MDKF Strategy with DOFS

- **PGD model** [Vitse *et al.*]
  - 4-points bending test
  - prediction of damage






damage
-1.981e-04
0.25
0.5
0.75
1.000e+00
0
-0.0002
-0.0004
-0.0006
-0.0008
-0.001
-0.0012
-0.0014
-0.0016
0 10 20 30 40 50 60 70 80 90 100
3.5e+06
3e+06
2.5e+06
2e+06
1.5e+06
1e+06
500000
0
-500000
0 5e-05 0.0001 0.00015 0.0002 0.00025 0.0003 0.00035 0.0004 0.00045 0.0005 0.00055
μ_1 young modulus
μ_2 loading amplitude
PXDMF Reader
A Separated Variable Reader for ParaView


damage
-1.981e-04
0.25
0.5
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1.000e+00
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-0.0002
-0.0004
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μ1 young modulus
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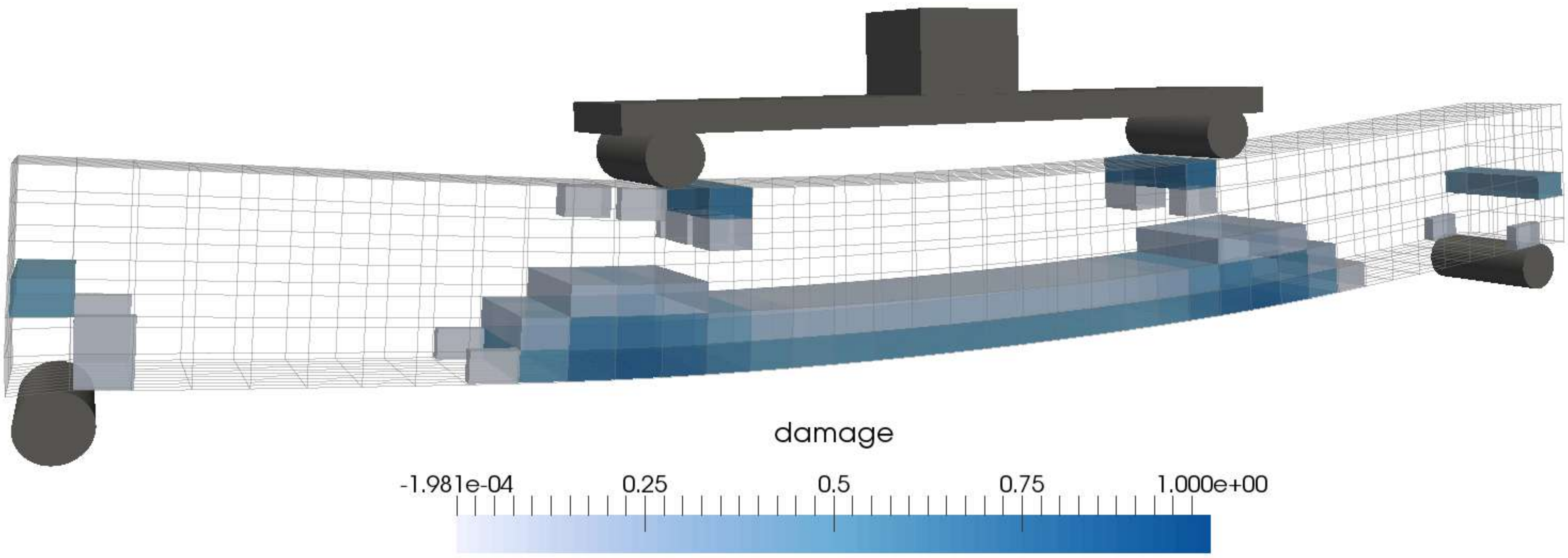

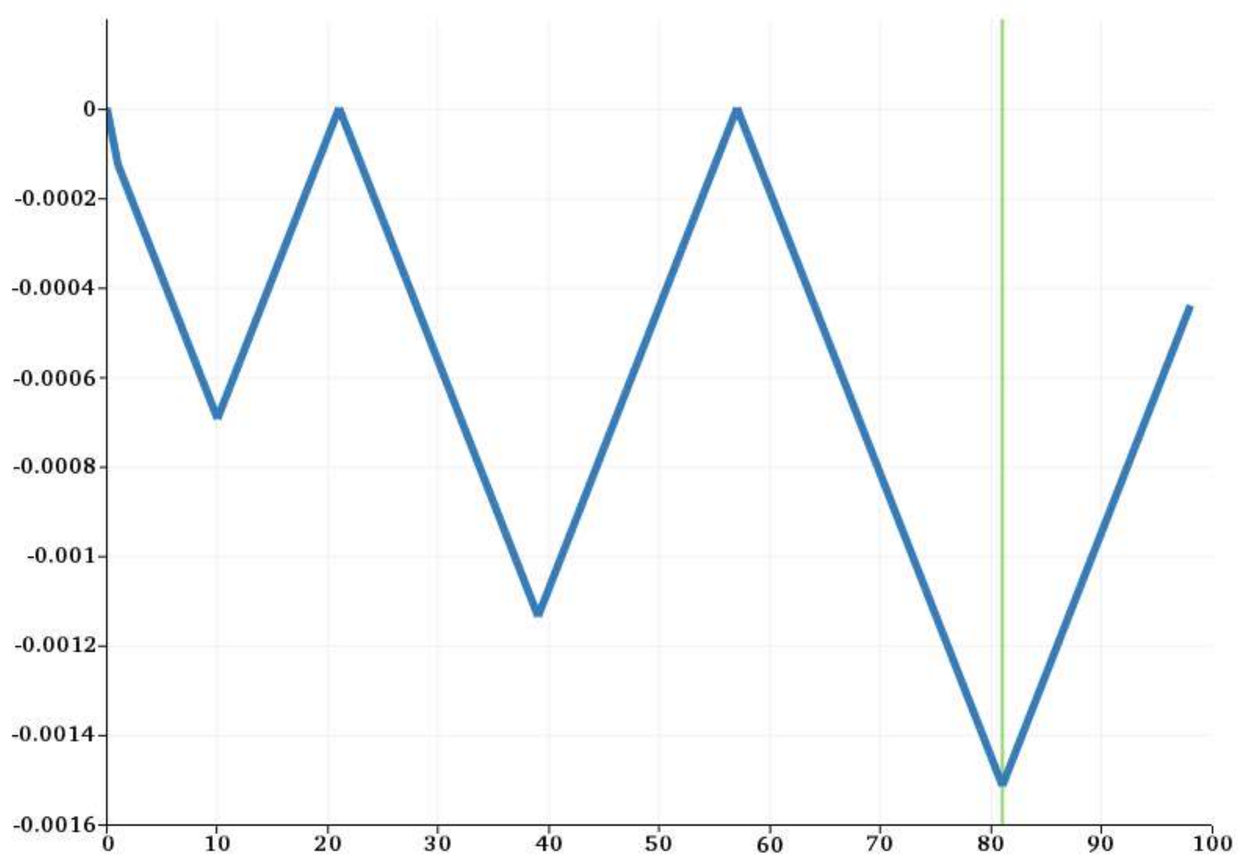

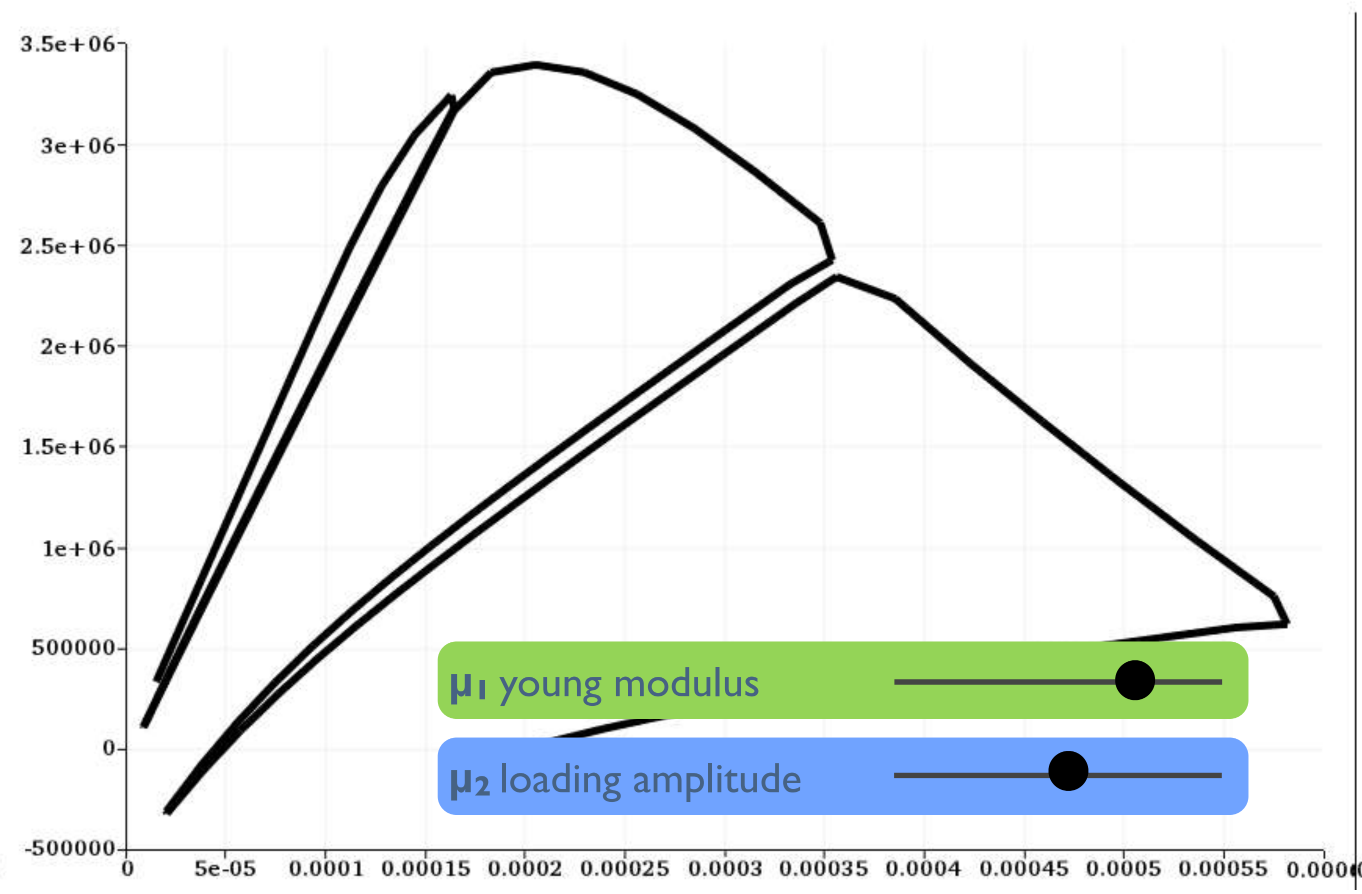

PXDMF Reader

A Separated Variable Reader for ParaView

Task 2: Enrichment with Physics-Augmented NNs

- Learning constitutive laws = active topic, large recent literature (PINNs, TANNs,…)

Raissi *et al.,* Physics-informed NNs: a deep learning framework for solving forward and inverse problems involving nonlinear PDEs (2019)
Huang et al., Learning constitutive relations from indirect observations using deep neural networks (2020)
Hernandez et al., Structure-preserving neural networks (2021)
Masi *et al.*, Thermodynamics-based ANNs for constitutive modeling (2021)
Asad *et al.*, A mechanics-informed ANN approach in data-driven constitutive modeling (2022)
Klein *et al.*, Polyconvex anisotropic hyper elasticity with neural networks (2022)
Thakolkaran et al., NN-EUCLID: deep learning hyper elasticity without stress data (2022)
Linden et al., Neural networks meet hyper elasticity: a guide to enforcing physics (2023)

Physics-guided architecture

- Intermediate layers can be interpreted as physical quantities that can be used in the loss function.
- Possible to impose properties such as convexity, invariance…
- **A thermodynamics-consistent architecture**

Physics-guided loss function

$$\mathcal{L} = \mathcal{L}_{\text{data}} + \mathcal{L}_{\text{phy}}$$

- “PINN” : Physics informed neural network (Raissi 2019)
- **The modified constitutive relation error**

Physics-guided initialization

- Amount of data needed is a problem : it is possible to first train the network with synthetic data generated with a physical a priori, close to the “true solution”, before training with experimental data
- **Initialization with linear isotropic law**

→ The mCRE framework naturally integrates all recent trends
→ No need for strain-stress (or strain-free energy) database

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Task 2: Enrichment with Physics-Augmented NNs

■ General strategy (NN-mCRE)

PyTorch

- Generalized standard materials [Halphen & Nguyen 1975]

$$\mathbf{s} = \frac{\partial \psi}{\partial \mathbf{e}_e} \quad ; \quad \mathbf{s} = \frac{\partial \varphi}{\partial \dot{\mathbf{e}}_p}$$

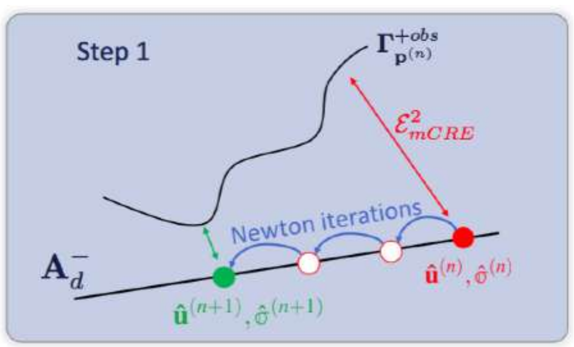
state equations ; evolution laws

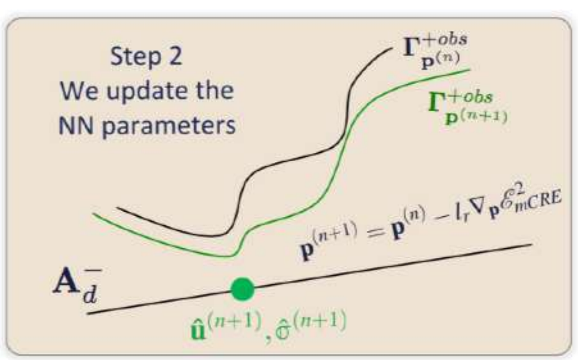
$$\boxed{\mathcal{E}^2_{CRE|t} = \int_\Omega \eta_\psi(\hat{\mathbf{e}}_e, \hat{\mathbf{s}}) + \int_0^t \int_\Omega \eta_\varphi(\dot{\hat{\mathbf{e}}}_p, \hat{\mathbf{s}})}$$

with

$$\eta_\psi(\hat{\mathbf{e}}_e, \hat{\mathbf{s}}) = \psi(\hat{\mathbf{e}}_e) + \psi^*(\hat{\mathbf{s}}) - \hat{\mathbf{s}} \cdot \hat{\mathbf{e}}_e$$
$$\eta_\varphi(\dot{\hat{\mathbf{e}}}_p, \hat{\mathbf{s}}) = \varphi(\dot{\hat{\mathbf{e}}}_p) + \varphi^*(\hat{\mathbf{s}}) - \hat{\mathbf{s}} \cdot \dot{\hat{\mathbf{e}}}_p$$

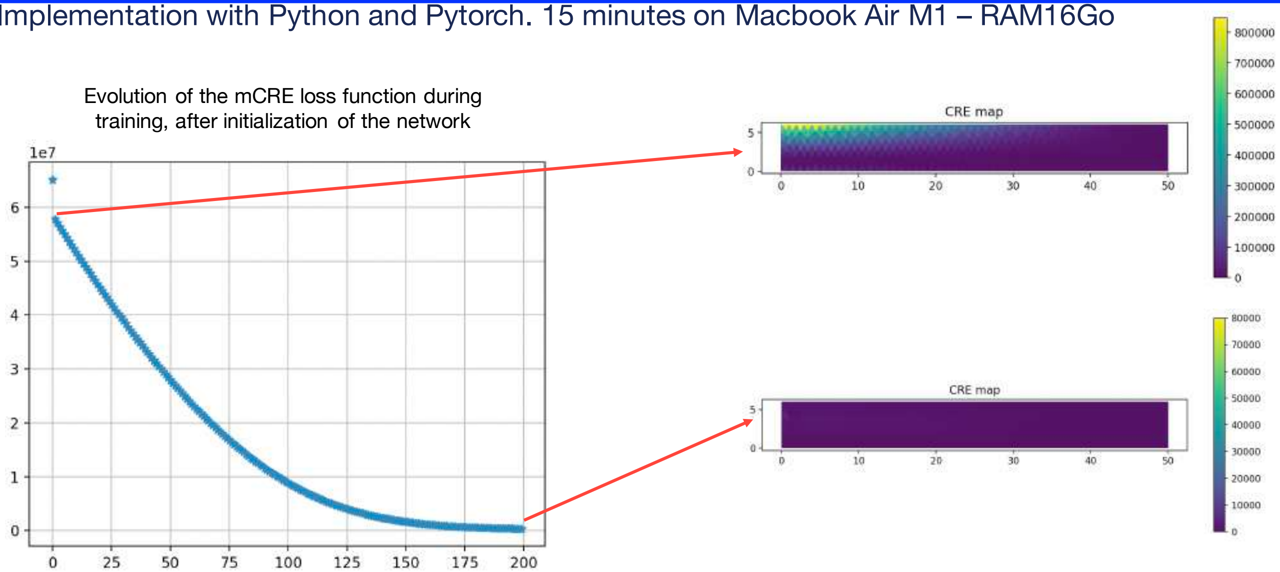
- **unsupervised** strategy to learn potentials (+ internal variables) and correct model bias
- **thermodynamics-consistent** architecture (ICNNs [Amos 2016]), with mCRE loss function

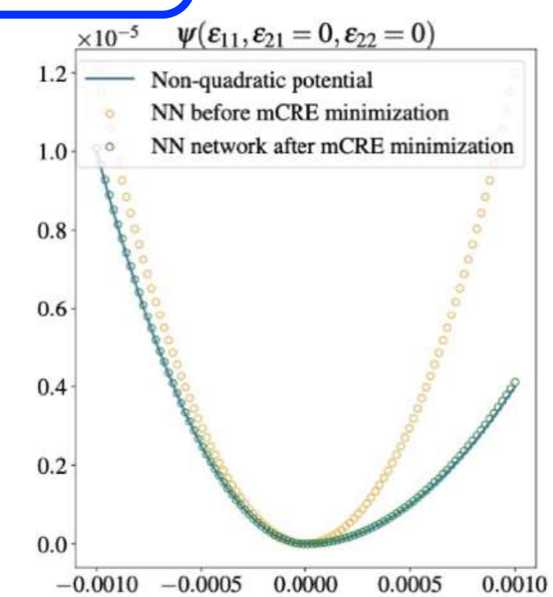




- Truth: $\psi(\varepsilon) = \frac{1}{2}E_1(1-d_1) < \epsilon_{11} >^2_+ + \frac{1}{2}E_1 < \epsilon_{11} >^2_- + \frac{1}{2}E_2\, \epsilon^2_{22} + G\, \epsilon^2_{21}$
- Initial guess: $\psi(\varepsilon) = \frac{1}{2}E_1\, \epsilon^2_{11} + \frac{1}{2}E_2\, \epsilon^2_{22} + G\, \epsilon^2_{21}$

- Implementation with Python and Pytorch. 15 minutes on Macbook Air M1 – RAM16Go





A. Benady, E. Baranger, L. C., NN-mCRE: A modified Constitutive Relation Error framework for unsupervised learning of nonlinear state laws with physics-augmented Neural Networks, *IJNME*, 125(8):e7439 (2024)
A. Benady, E. Baranger, L. C., Unsupervised learning of history-dependent constitutive material laws with thermodynamically-consistent neural networks in the modified Constitutive Relation Error framework, *CMAME*, 425:116967 (2024)

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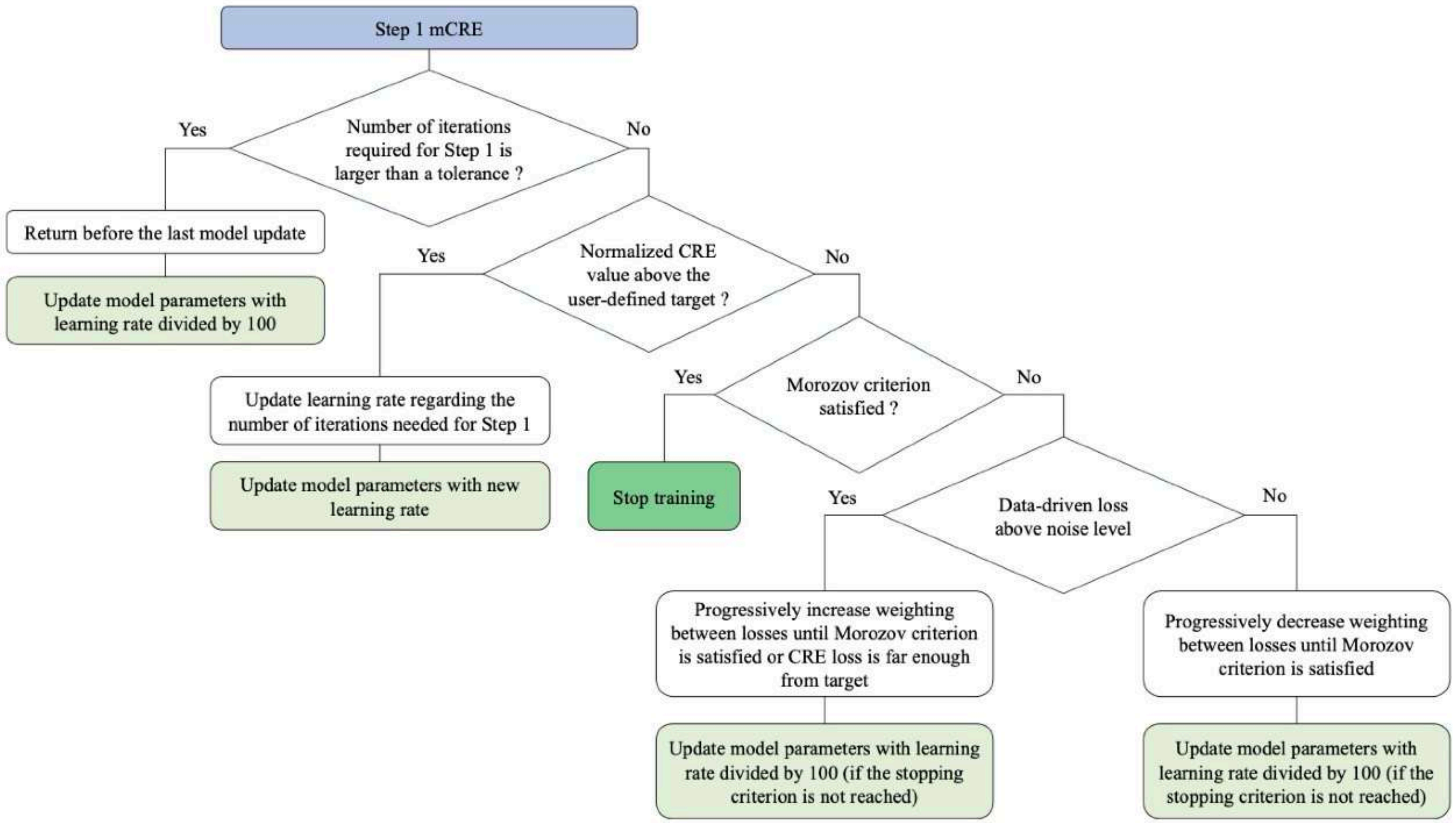
Task 2: Enrichment with Physics-Augmented NNs

- **Automatic adaptive tuning of hyper-parameters**

Parameters	Strategy
learning rate	related to the number of iterations at Step 1
weighting in the loss	set using the Morozov principle (related to noise)
number of epochs	stop criteria based on the CRE modeling error term
NN initialization	trained from simple potential (e.g., linear isotropic elasticity)
batch size	fixed by the mesh (one batch is the whole structure)

→ parameters updated during the training



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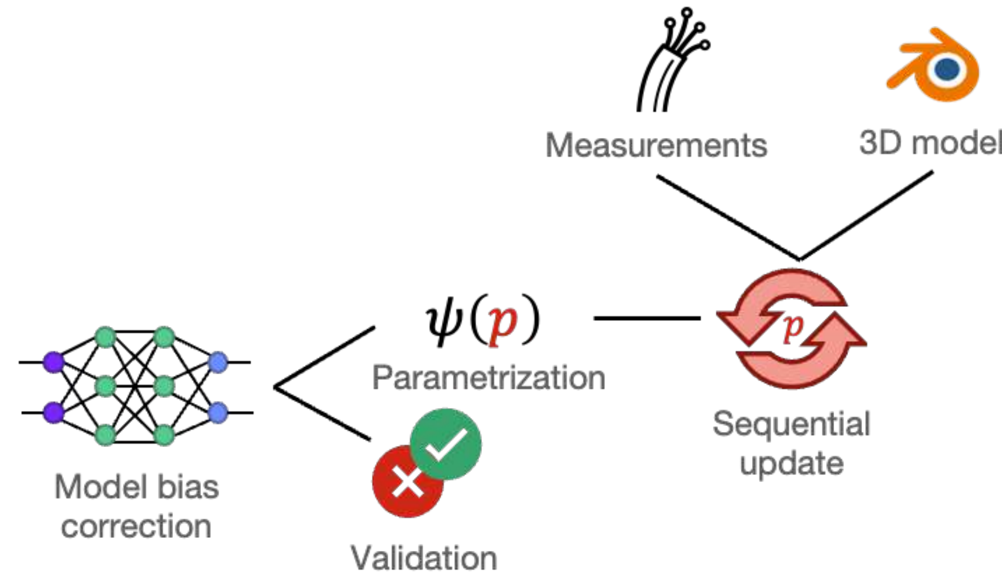
Task 2: Enrichment with Physics-Augmented NNs



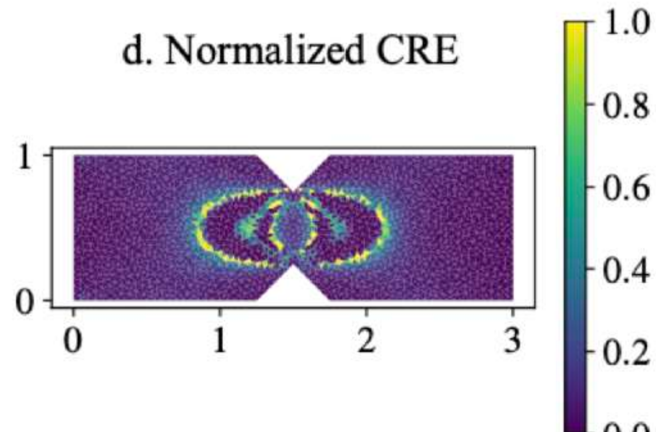
Connexion with MDKF

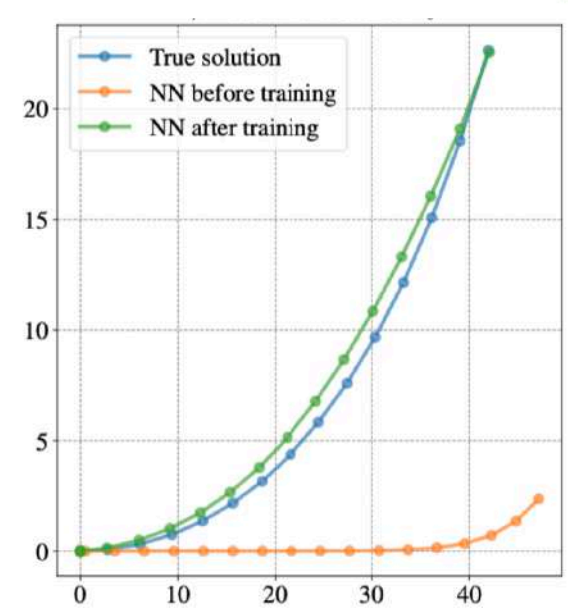
→ explicit, low-parameter expressions of (ψ, φ)

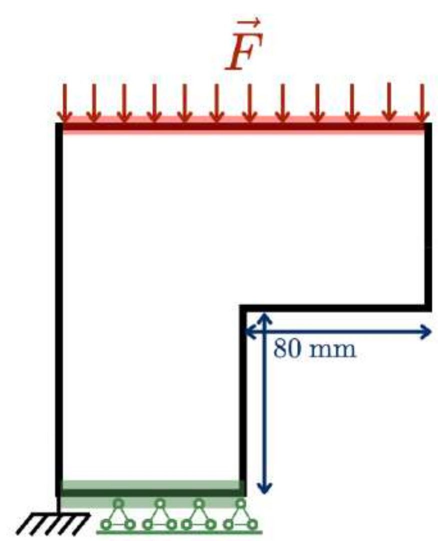
symbolic regression [Cranmer 2023]

extreme sparsification [Fuhg *et al.* 2024]

Model validation



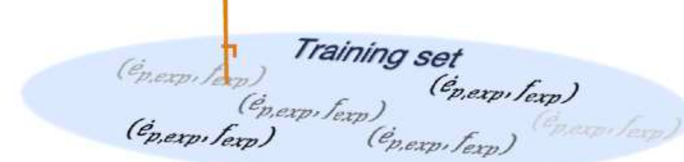


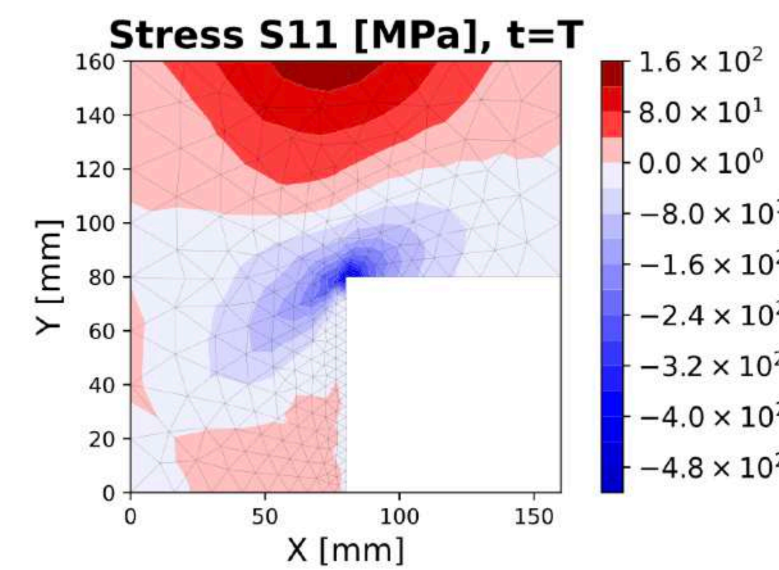


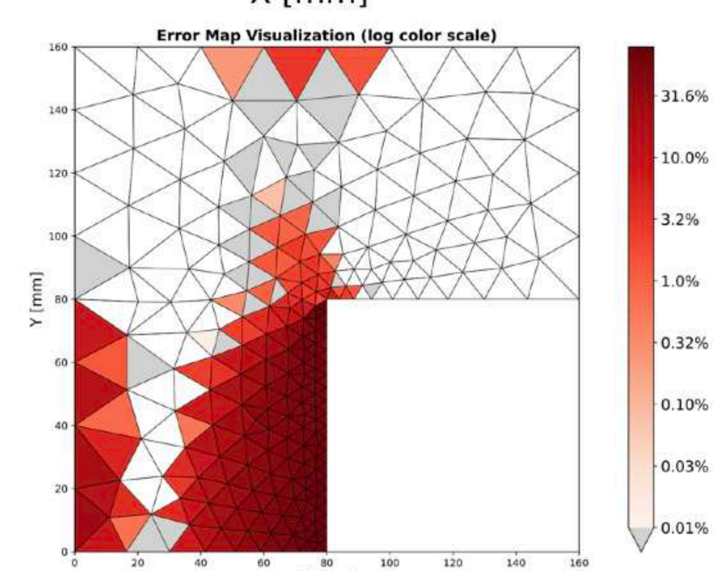
New computation on a new structure

$\overline{\dot{e}_p} = (\overline{\dot{\epsilon}_p}, \overline{-\dot{p}})$

$\overline{f} = (\overline{\sigma}, \overline{R})$



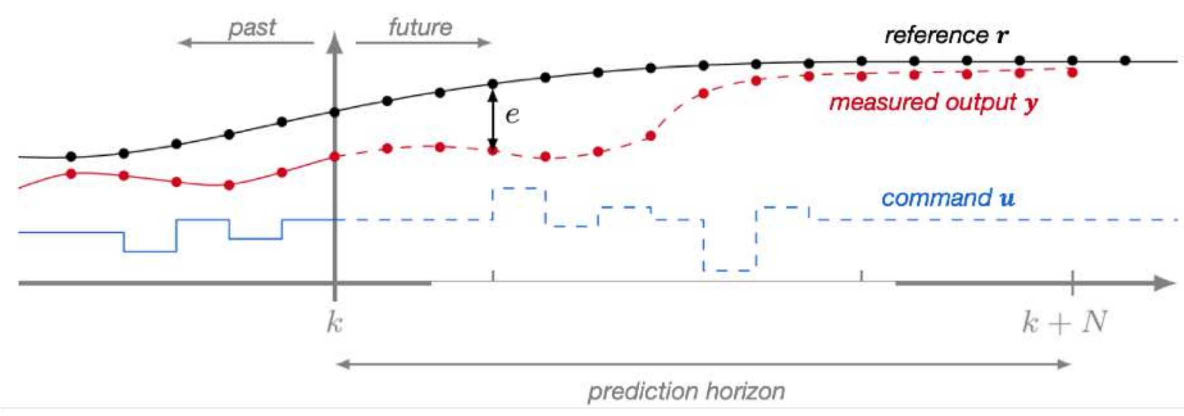


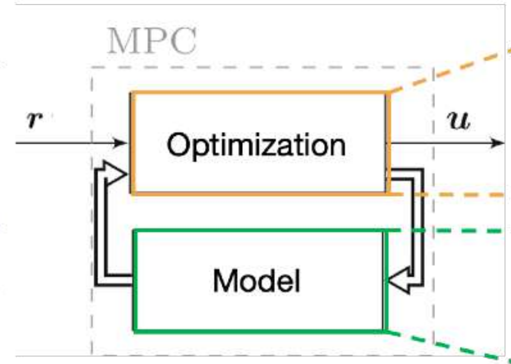


P. Ladevèze, L. C., From data to reality: criteria for the validation of data-driven models for history-dependent materials, *European Journal of Mechanics / A Solids*, 118:106095 (2026)

Task 3: Guaranteed Online Command Synthesis

- Use of Model Predictive Control (MPC) for integrated feedback with evolutive systems
- Solution of an optimization problem at each control time (with constraints)
- State given by **optimal admissible fields of mCRE** (MDKF) + UQ





$$u = \arg\min_{u} \quad J(x,u) = \sum_{i=1}^{N} \|r(k+i) - y(k+i)\| + \alpha\|\Delta u(k+i)\|$$

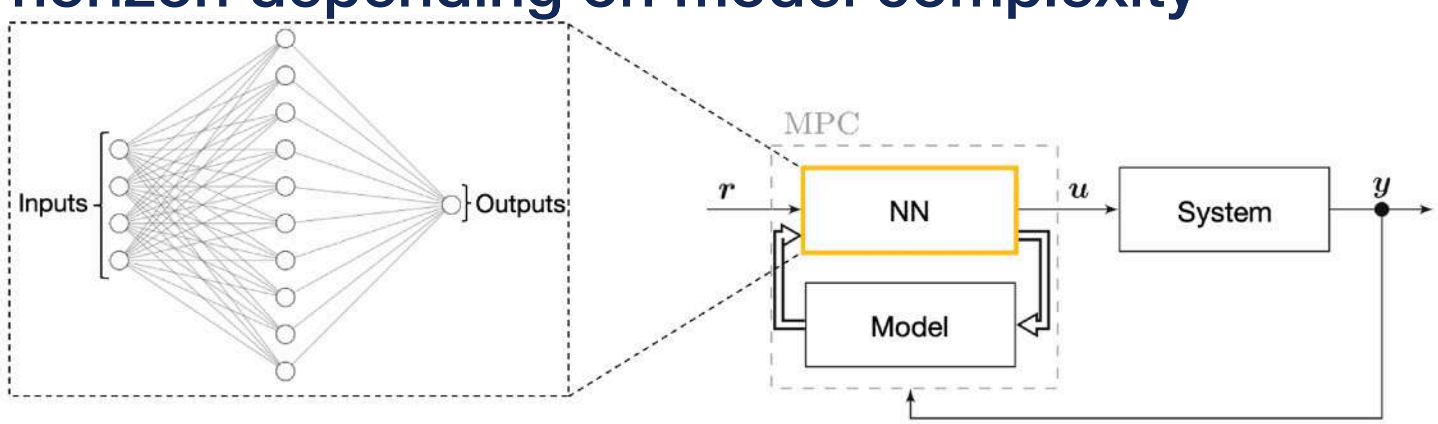
$$x(k+1) = f(x(k), u(k))$$
$$y(k) = h(x(k))$$

COSTLY!!!

MPC toolbox [Fiedler 2023] / CasADi
Interior Point Method [Nesterov 1997]

- Data-driven MPC with underparametrized NNs (for real-time, high dimension,…)
  - AI used to mimic MPC optimization (policy) and quickly compute the command
  - supervised learning from MPC simulation / unsupervised learning
  - guaranteed convergence for the training error (using NTK matrix)
  - online adaptation of the horizon depending on model complexity

1 hidden layer (128 neurons)
Trained with Adam (3000 epochs)



D. Martin-Xavier, L. C., L. Fribourg, Training and generalization errors for underparametrized neural networks, *IEEE Control Systems Letters,* 7:3926–3931 (2023)

D. Martin-Xavier, L. C., L. Fribourg, MPC surrogates based on supervised or unsupervised learning for the real-time control of nonlinear systems, *IFAC Journal of Systems and Control*, 36:100409 (2026)

Task 3: Guaranteed Online Command Synthesis

Application: Van der Pol oscillator

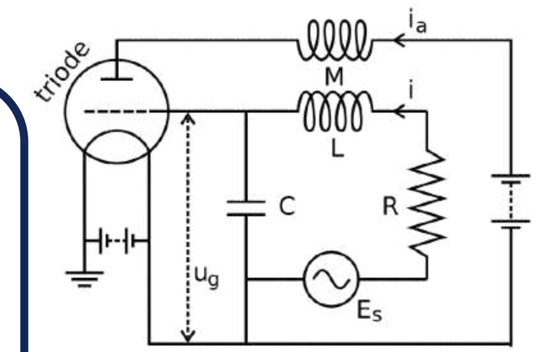
- **Model:** $$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = (1 - x_1^2)x_2 - x_1 - u \end{cases}$$

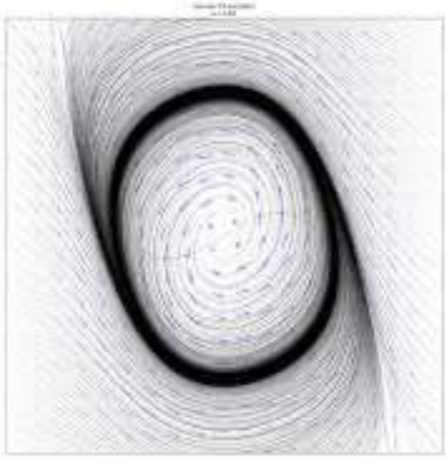
models oscillations of triodes in electrical circuits

where x_1 is the **position**, x_1^{ref} the **reference**, x_2 the **speed** and u the **command**.

- **Constraints :** $u \in [-1, 1]$ and $x_1, x_2 \in [-3, 3]$

- **Goal:** make the system converge towards a reference trajectory x_1^{ref}.

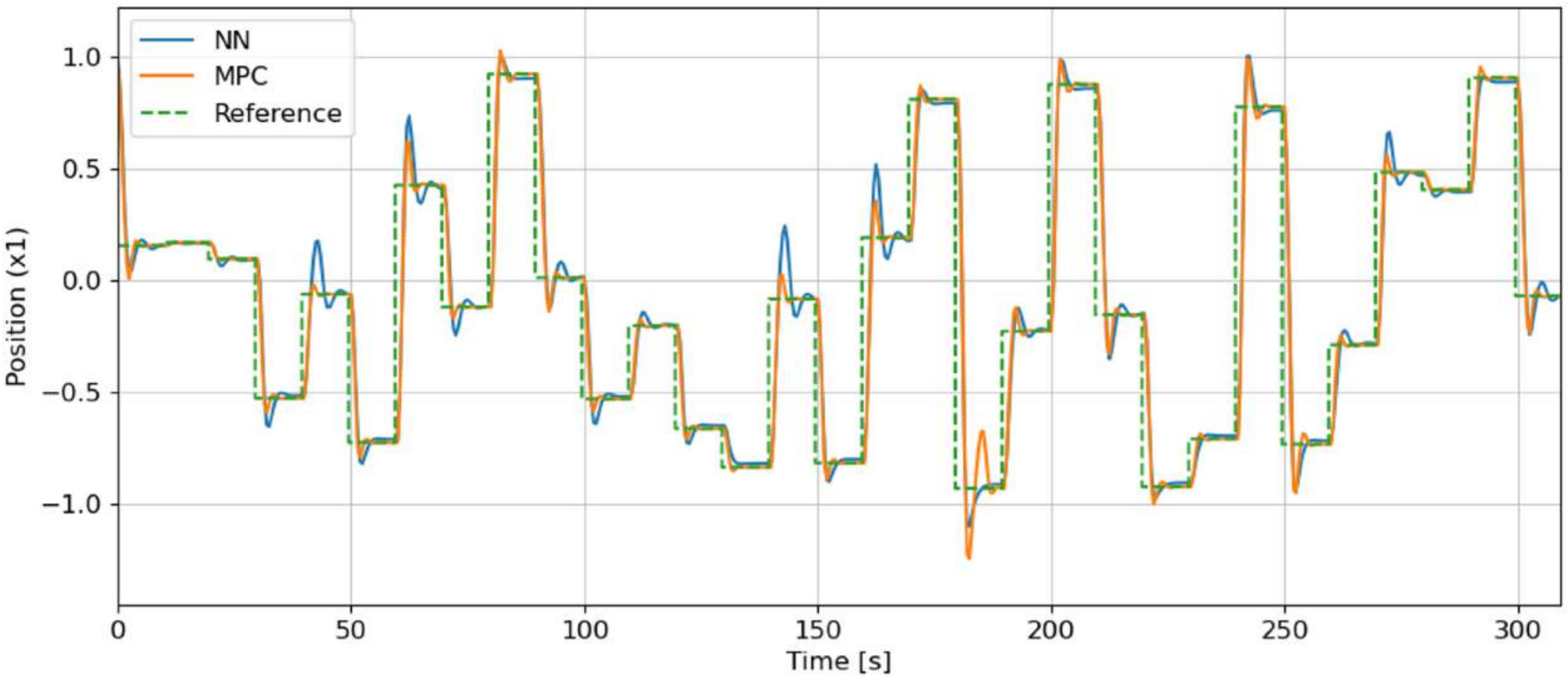




prediction horizon: $N = 5$
time step: $T_S = 0.5s$

initial condition: $\mathbf{x}_0 = [1, 0]$
scaling factor: $\alpha = 0.1$

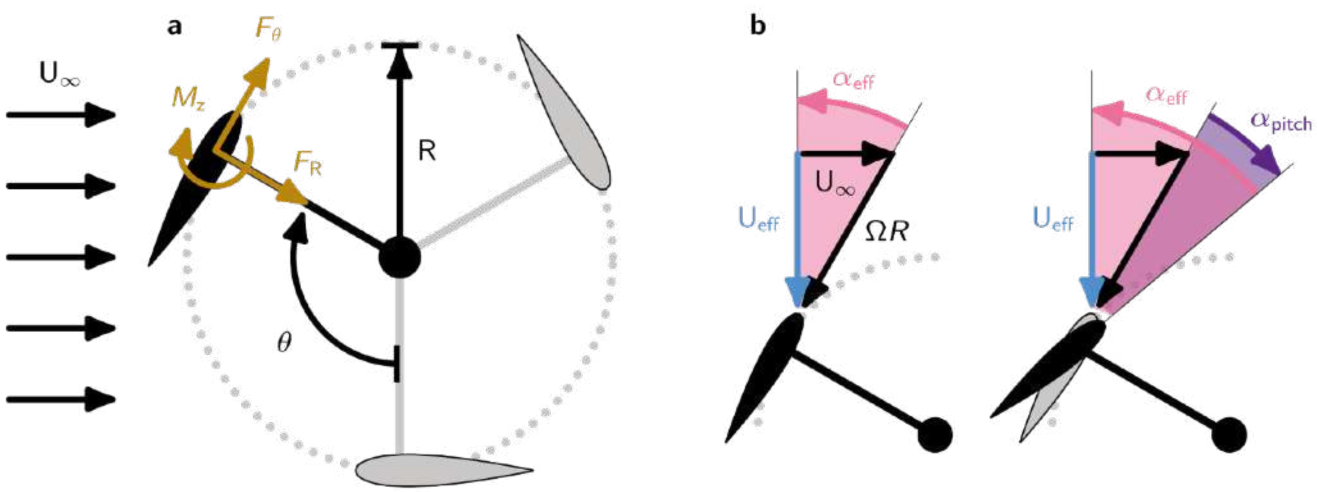
training set: $S_{train} = 6000$
test set: $S_{test} = 2000$

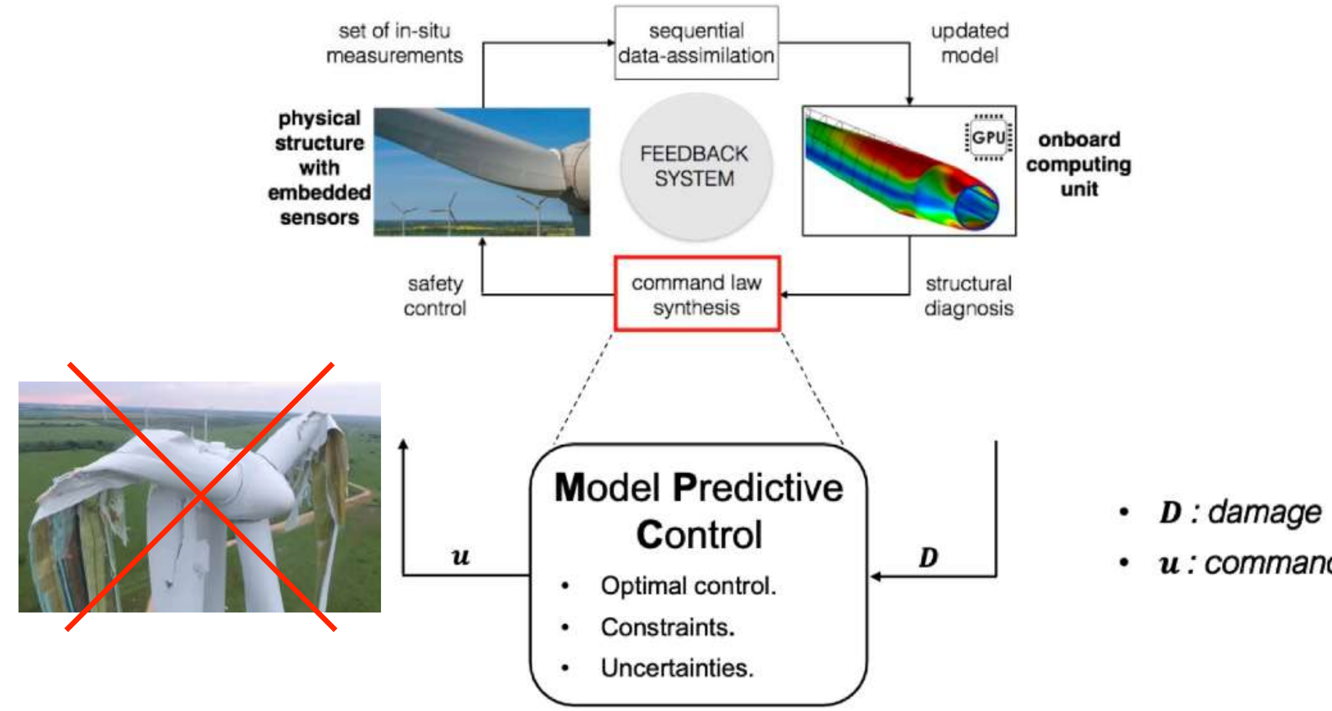


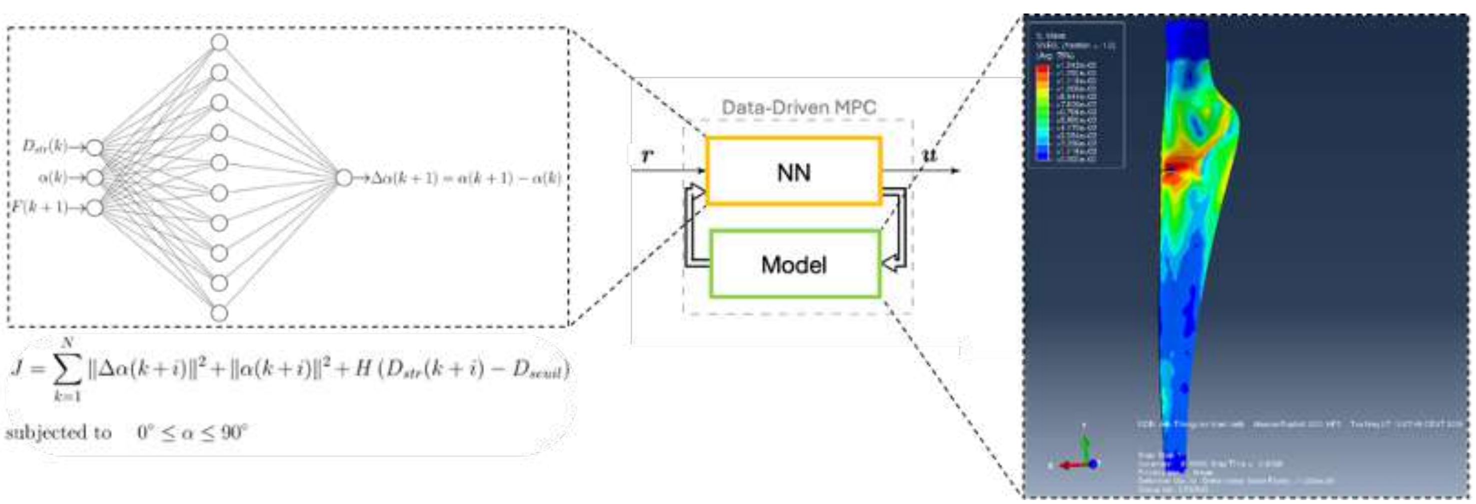
	MSE	CPU
MPC	0.066	2.34 ms
NN	0.067	0.17 ms

Task 3: Guaranteed Online Command Synthesis

- **Application: blade pitch control to manage damage evolution**







Tracking error

Setting	MPC	Supervised	Unsupervised
Noiseless	**2.05**[¶]	2.30 ± 0.07	2.34 ± 0.07
With noise	$\mathbf{3.6 \pm 0.2}$	4.3 ± 0.2	4.2 ± 0.1

Runtime

Setting	MPC	Supervised	Unsupervised
Noiseless	56.2 ± 0.9	2.10 ± 0.08	$\mathbf{1.90 \pm 0.04}$
With noise	56.8 ± 0.5	2.15 ± 0.09	$\mathbf{1.93 \pm 0.02}$

25× faster

- multiple outputs and long horizons $(N = 80)$
- stochastic disturbances (wind gusts)

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UQ with Tube MPC - Basics

Objective: robustness of the control (ensuring hard constraints) w.r.t. additional uncertainties

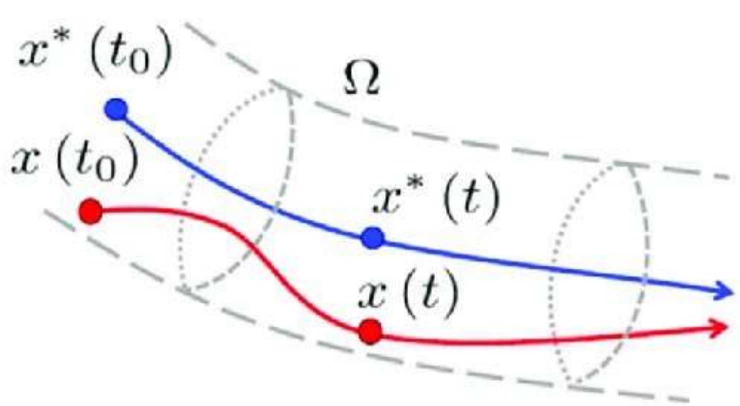
model bias, disturbances/noise, parametric uncertainty,…(stochastic variations)

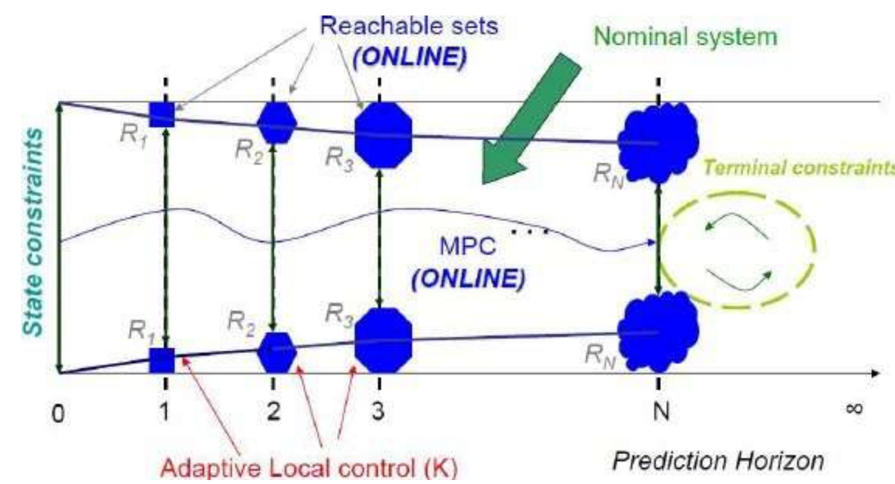
$$\dot{\mathbf{x}}(t) = F(\mathbf{x}(t), \mathbf{u}(t)) + \mathbf{w}(t) \qquad\qquad \mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t) + \mathbf{w}_t$$

⟶ computation of a sequence of state space regions (reachability tube) [Mayne *et al.* 2009]

region around the nominal prediction that contains the system state under any uncertainty
calculation at each step within the prediction horizon (set of reachable sets)

⟶ maintain all possible trajectories of the uncertain system close to reference





Combination of controllers: nominal MPC controller + ancillary feedback controller

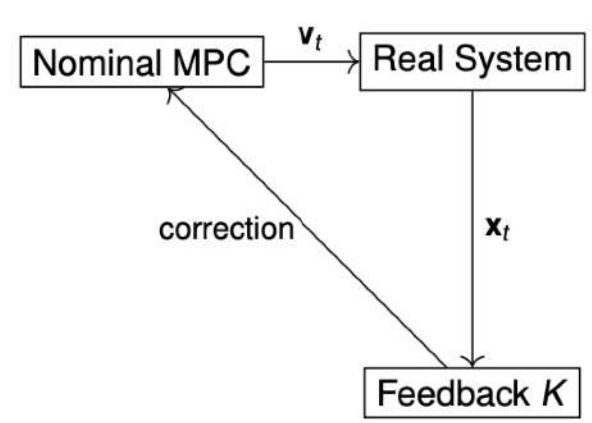
$$\boxed{\mathbf{u}_t = \mathbf{v}_t + \mathbf{K}(\mathbf{x}_t - \mathbf{z}_t)}$$

nominal control
from disturbance-free system

feedback obtained from a Ricatti equation
(unchanged with NN)

real trajectory

nominal trajectory



UQ with Tube MPC - Analysis

[Sivalingam *et al.* 2026]

➡ Analysis of the effect of NN approximation on the structure & behavior of tube MPC

- Takes ideas from statistical ML and contraction theory (contractive dynamics systems)

- Approximation error considered as another perturbation on the control
  ⟶ *enlarged tube*

- Bound on the worst-case error in terms of the NN generalization error

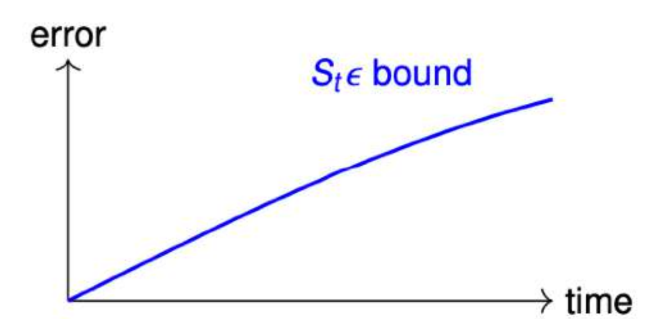
$$\boldsymbol{\delta}_t = \mathbf{z}_{NN,t} - \mathbf{z}_t \qquad \|\mathbf{z}_{NN,t} - \mathbf{x}_t^r\| \leq S_t\epsilon + e_t^r$$

$$\|\boldsymbol{\delta}_{t+1}\| \leq L_z\|\boldsymbol{\delta}_t\| + L_v\epsilon$$

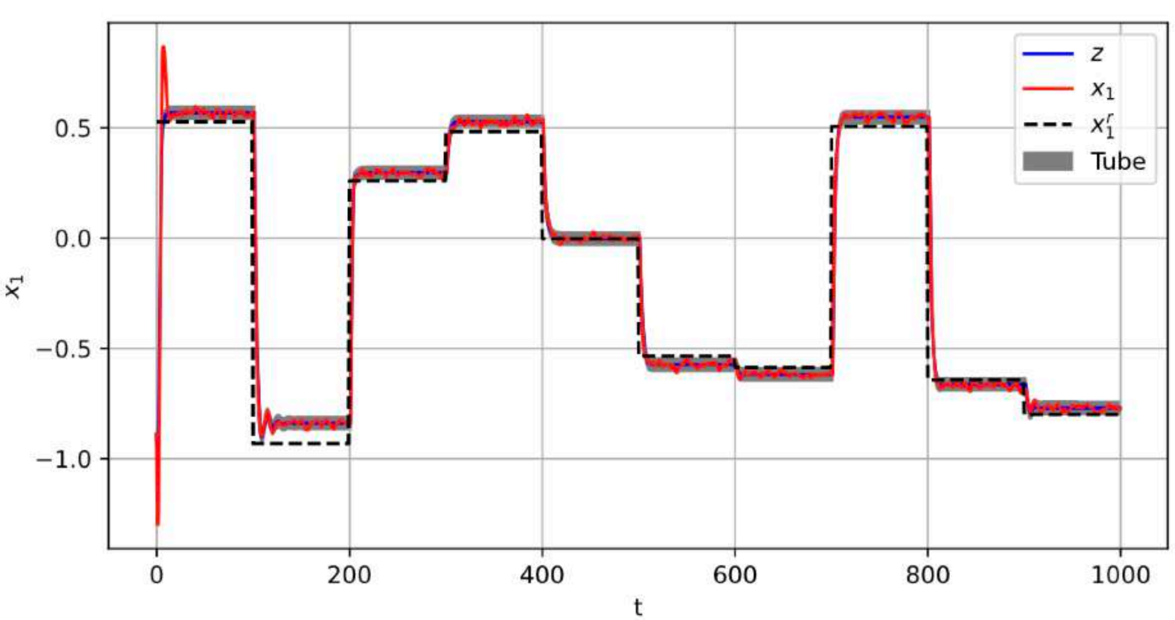
$$\|\boldsymbol{\delta}_t\| \leq S_t\epsilon$$ (with inflation factor)

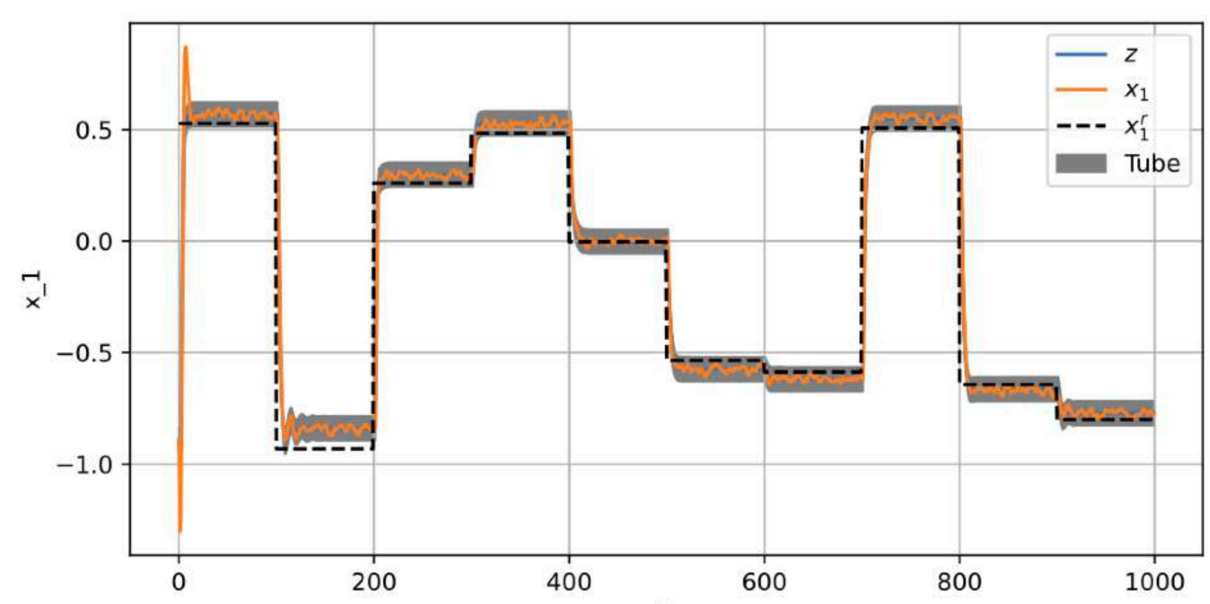
NN error

MPC tracking error

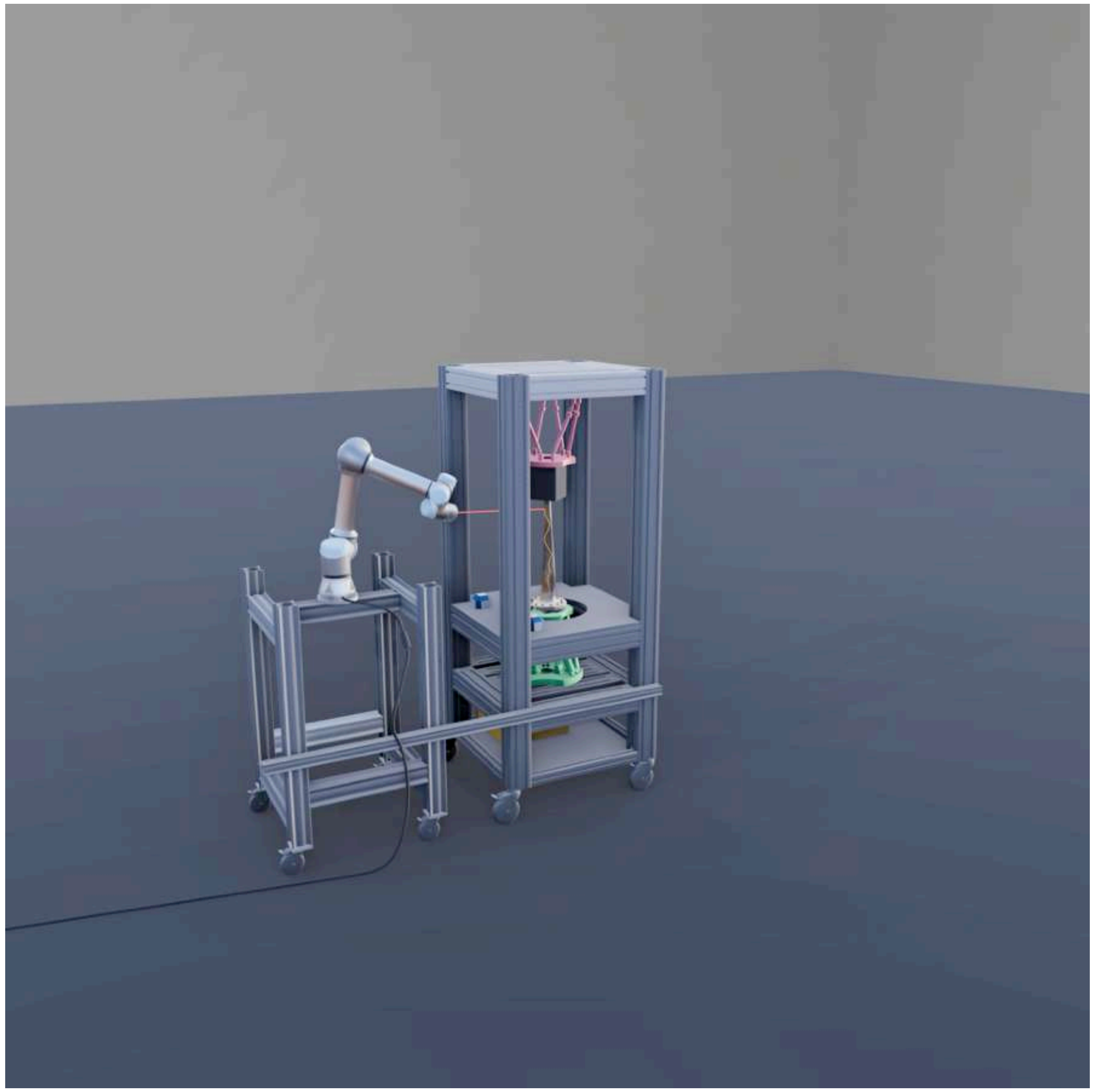


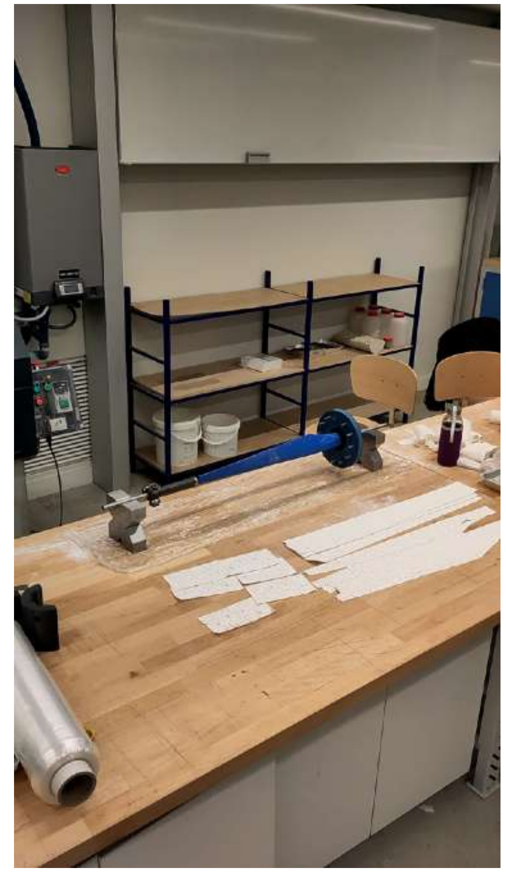
<u>Van der Pol oscillator with/without external disturbances</u>

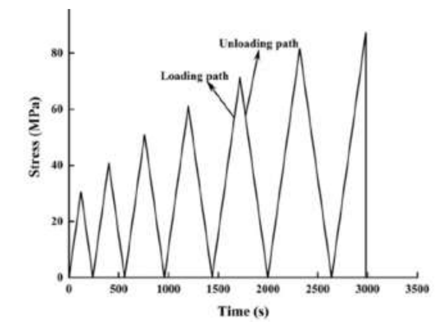


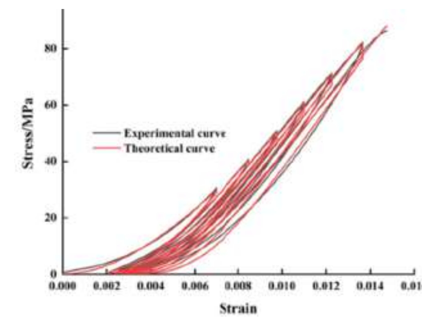


First Version of the POC









blender RoboDK

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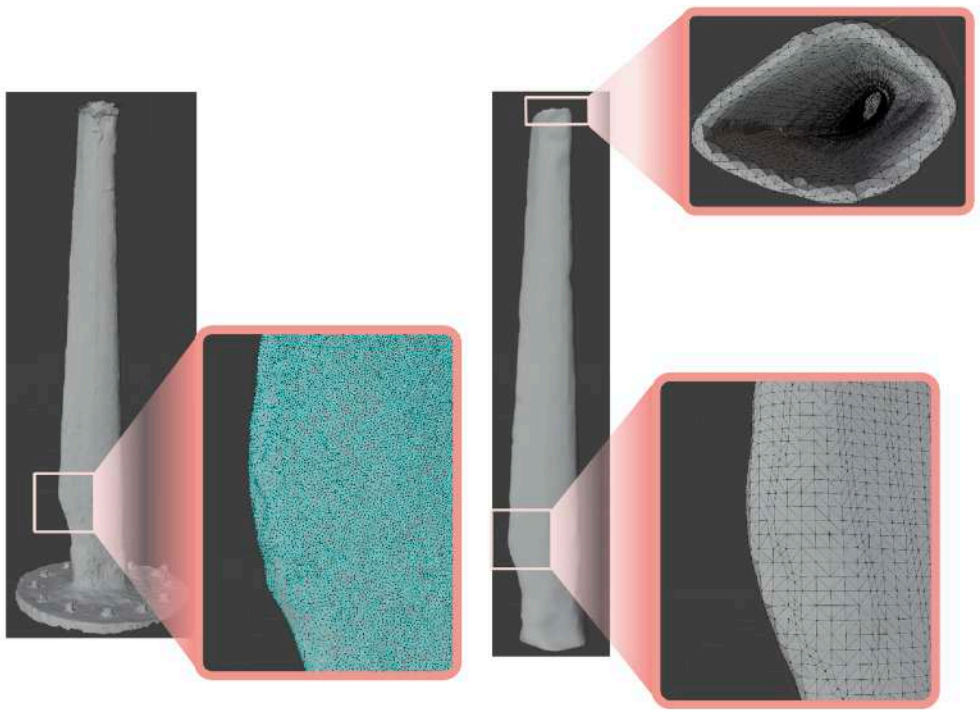
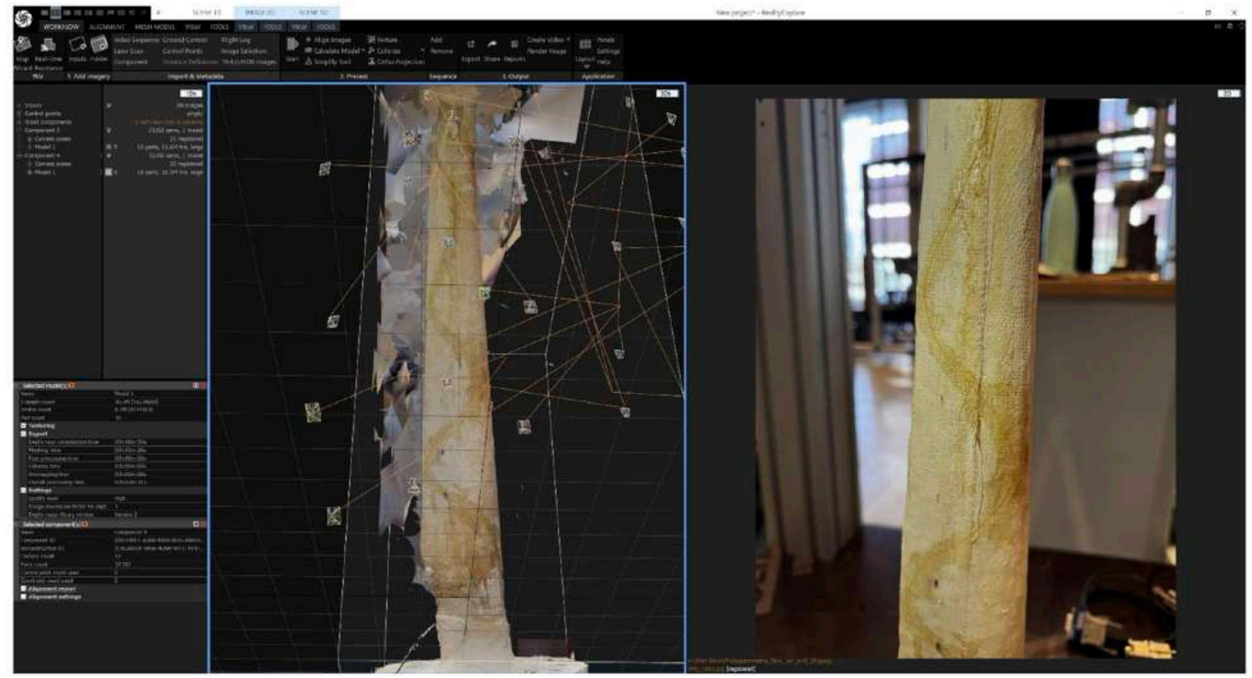
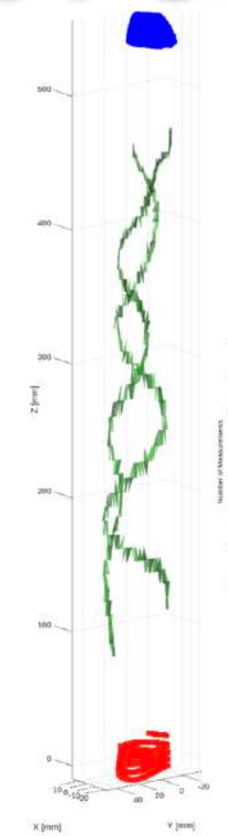
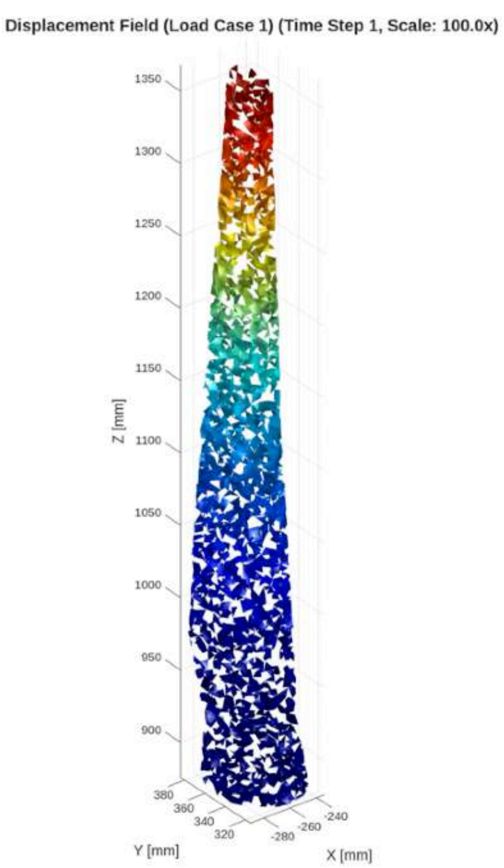
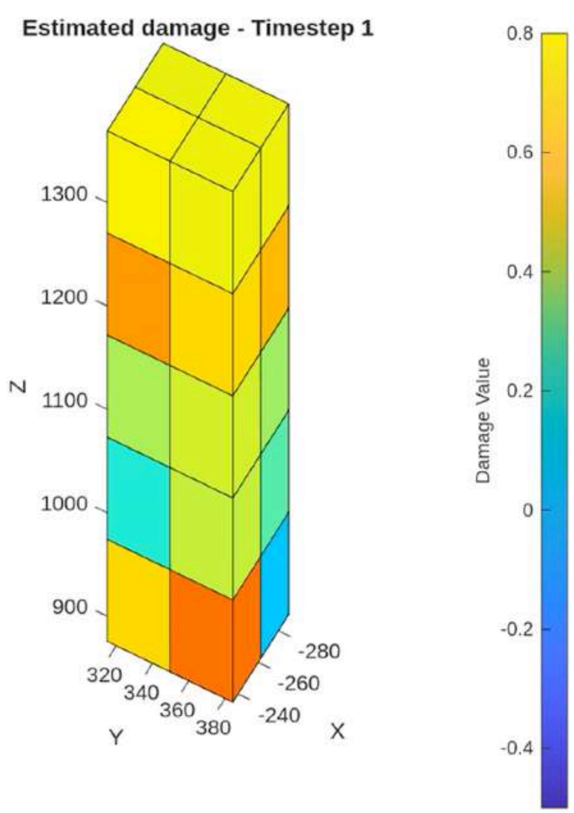
First Version of the POC

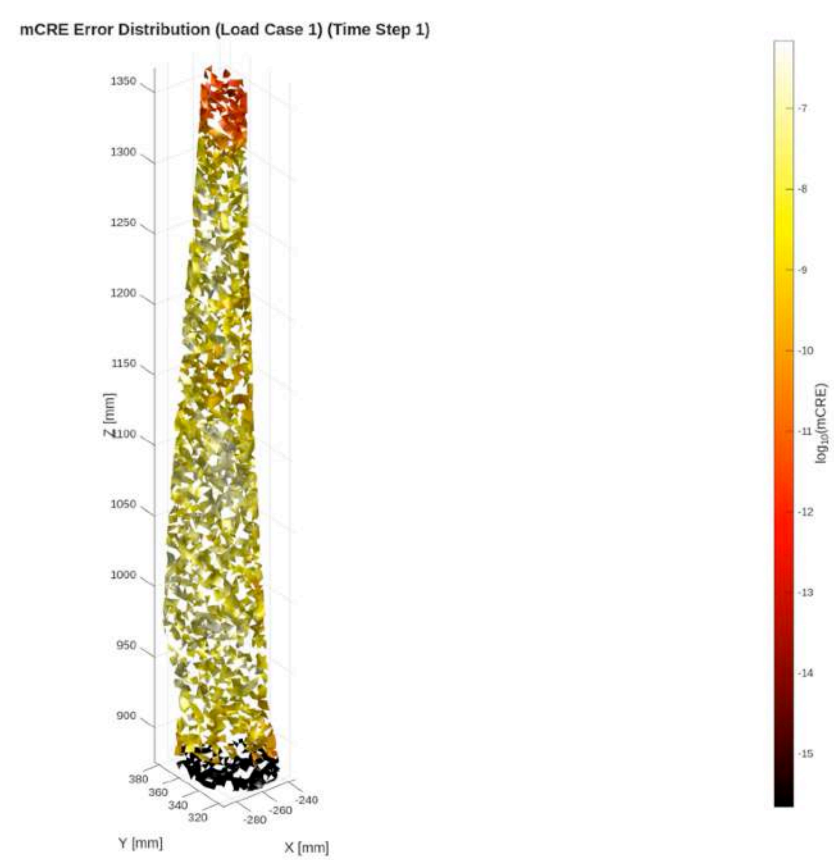


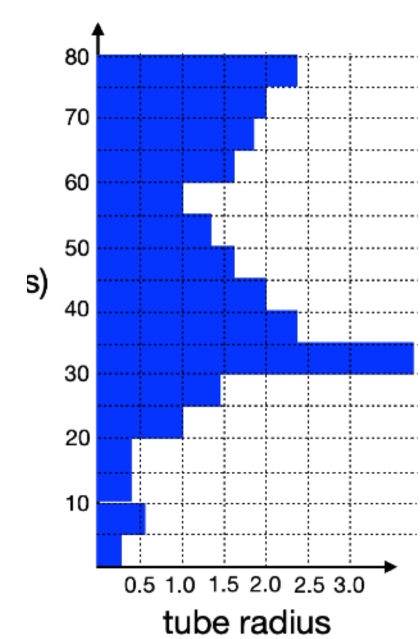










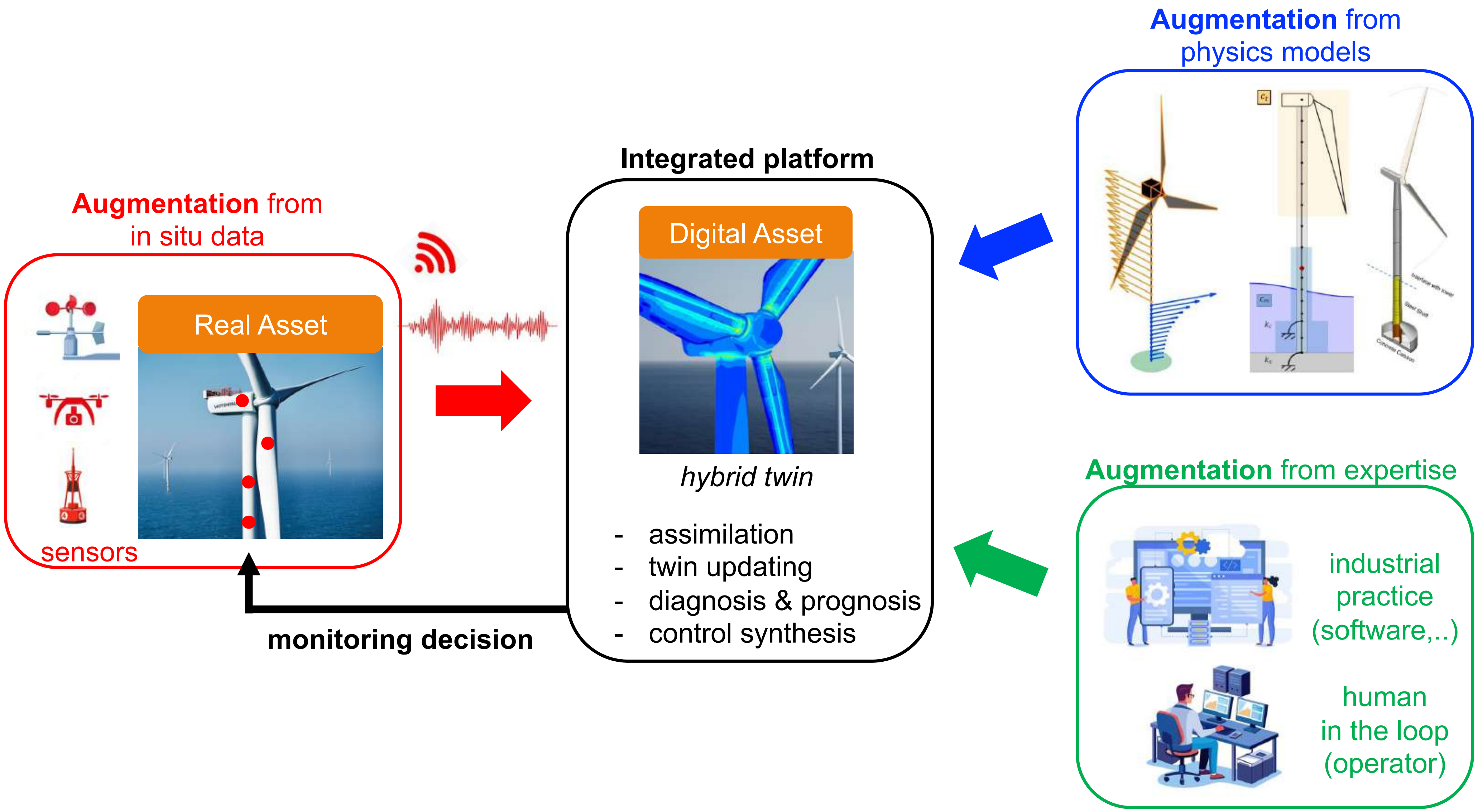


Assimilation (MDKF) + Control (MPC): 0.04-3 s

What Is Next?

INCREASER (ERC-PoC, 2026-2028)

Integrated Computational Platform for Efficient Real-time Structural Monitoring and Decision Support from Augmented Digital Twinning



- hybrid twin-based monitoring and predictive maintenance for complex structures
- development of a multifunctional platform that integrates/implements ERC tools
- collaboration with industry, for evaluation and further commercial applications

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LMPS

THANK YOU !!!