7th International Electronic Conference on Sensors and Applications
15-30 November 2020

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A COMBINED MODEL-ORDER REDUCTION AND DEEP LEARNING APPROACH FOR STRUCTURAL HEALTH MONITORING UNDER VARYING OPERATIONAL AND ENVIRONMENTAL CONDITIONS

Matteo Torzoni[1,*], Luca Rosafalco[1], Andrea Manzoni[2]

[1] Dipartimento di Ingegneria Civile ed Ambientale, Politecnico di Milano, Italy;

[2] MOX, Dipartimento di Matematica, Politecnico di Milano, Italy;

* Correspondence: matteo.torzoni@polimi.it

GENOA (ITALY) 14/08/18, PARTIAL COLLAPSE OF THE MORANDI BRIDGE – 43 PEOPLE KILLED

Marco Grasso, Matteo Indice. Via all'anticipo del maxi-processo sul crollo. *Il secolo XIX*, 22/09/18.

MIAMI (FLORIDA, USA) 15/03/18, COLLAPSE OF A PEDESTRIAN FOOTBRIDGE - 6 PEOPLE KILLED

Pedro Portal. *Miami Herald, 15/03/18.*

HEALTH MONITORING UNDER VARYING OPERATIONAL AND ENVIRONMENTAL CONDITIONS

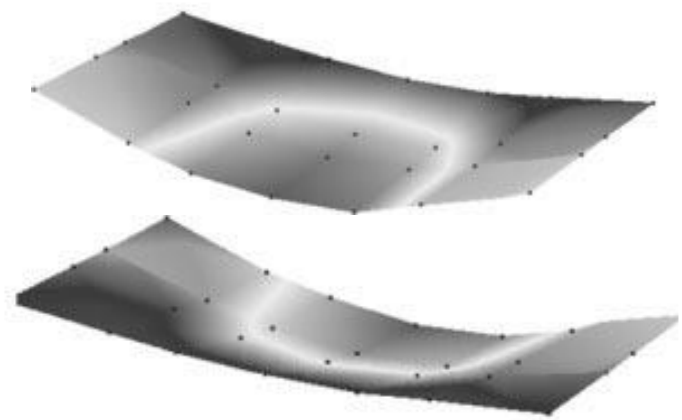
Sensor system recordings → **Structural Health Monitoring (SHM)** → Damage detection, localization and quantification

Sources of operational variability:

- load condition;
- load amplitude.

Sources of environmental variability:

- wind;
- humidity;
- **temperature** → expansion/contraction effect; softening/stiffening effect.



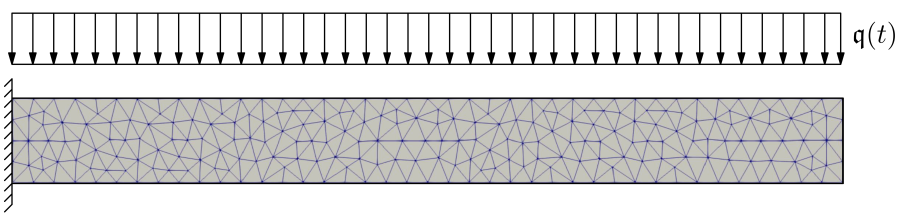
The Alamosa Canyon Bridge: 1st mode shape of one span of the Alamosa Canyon Bridge during two times of the day: morning (7.75 *Hz*); afternoon (7.42 *Hz*).

C. R. Farrar et al. Variability of modal parameters measured on the Alamosa Canyon bridge. Prodeedings of SPIE 1, 1997.

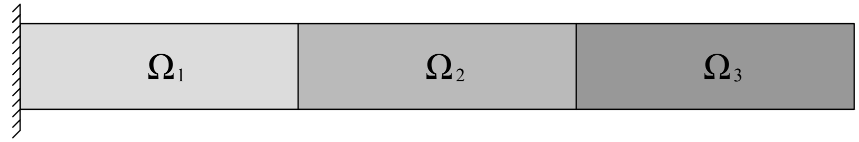
OBJECTIVE: DAMAGE LOCALIZATION UNDER VARYING OPERATIONAL AND ENVIRONMENTAL CONDITIONS

1. Simulation Based Classification: the problem is traced back to train a classifier on the basis of numerical data.

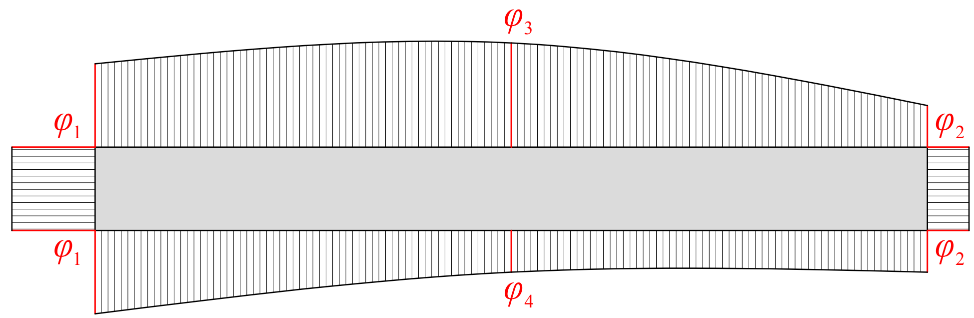
From reality to high fidelity FE modeling



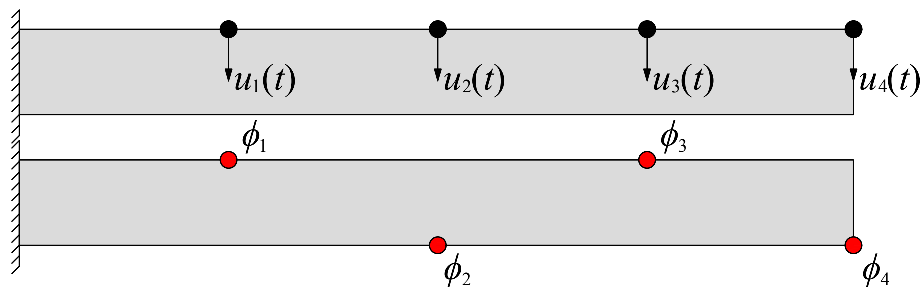
2. Damage: local stiffness reduction of predefined subdomains assumed fixed within the observation interval: **linear behavior.**



3. Thermo-meccanical effects are also simulated.



4. Processed data: vibrational signals shaped as multivariate time series and temperature measurements, both mimicking the recordings of a **pervasive sensor system**.



OFFLINE-ONLINE DECOMPOSITION

Evaluation of operational and environmental conditions

Evaluation of damage scenarios and sensors system design

FOM definition

ROM construction

Dataset generation

Training the classifier

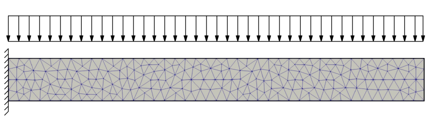
Test set generation

Testing the classifier

Offline phase

Online phase

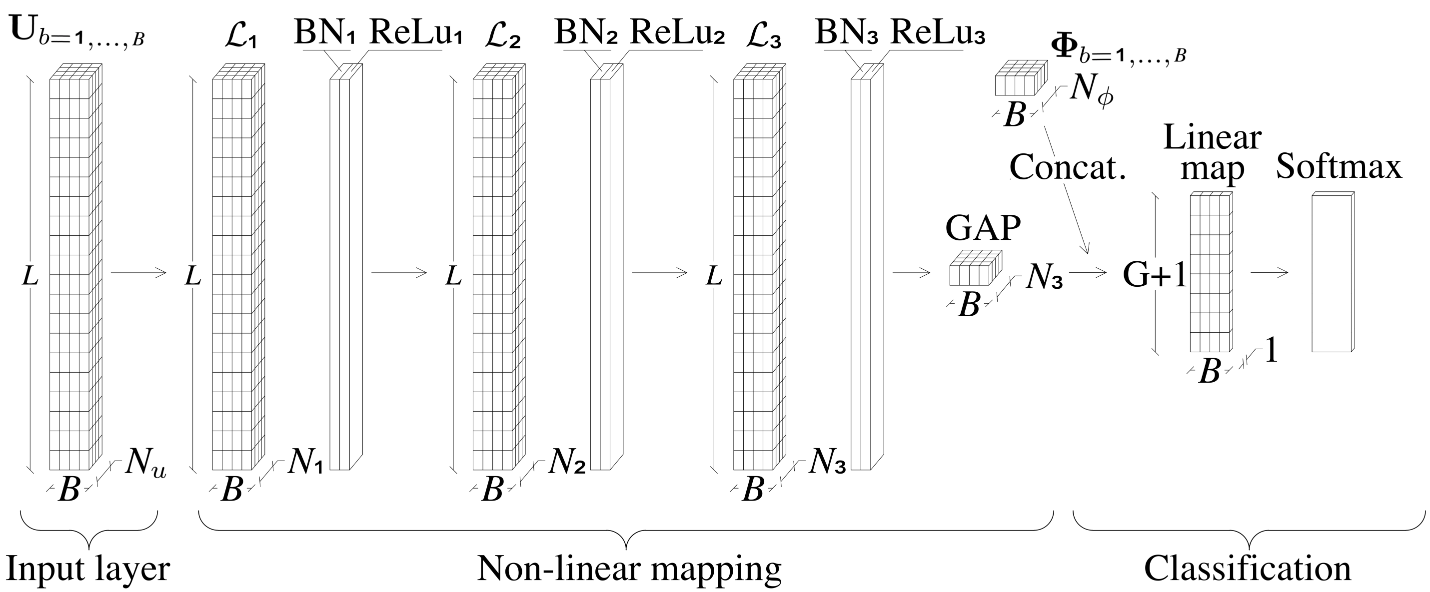
FOM = Full Order Model



ROM = Reduced Oreder Model
Combination of basis functions

FCN-BASED CLASSIFIER

- The **Dataset** includes instances of each considered damage state for several operational/thermal conditions.



Vibrational and temperature recordings → Underlying Mapping → Associated categorical label

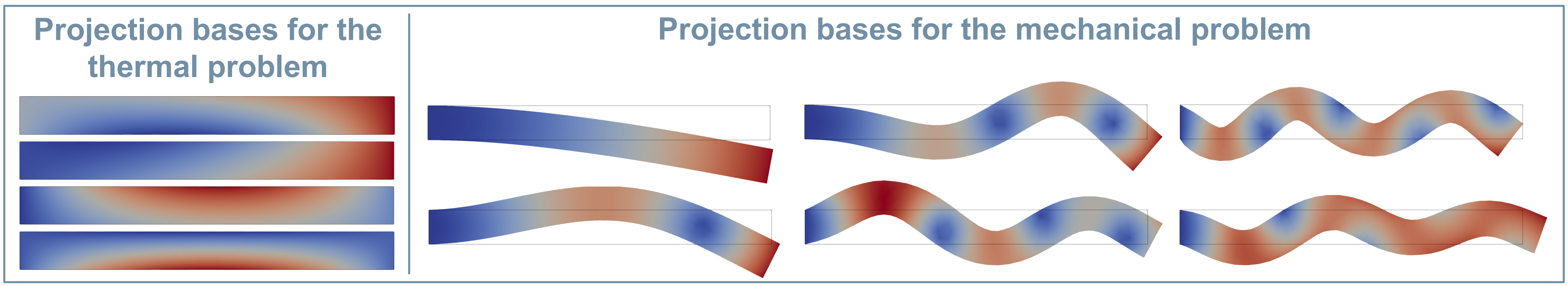
- **Training phase:** the classifier *learns* the **mapping** {input instance} ⇒ {associated label (damage state)}.

- **Testing phase:** the classifier should map unseen instance into the current damage condition.

FULL ORDER MODEL AND REDUCED ORDER MODEL

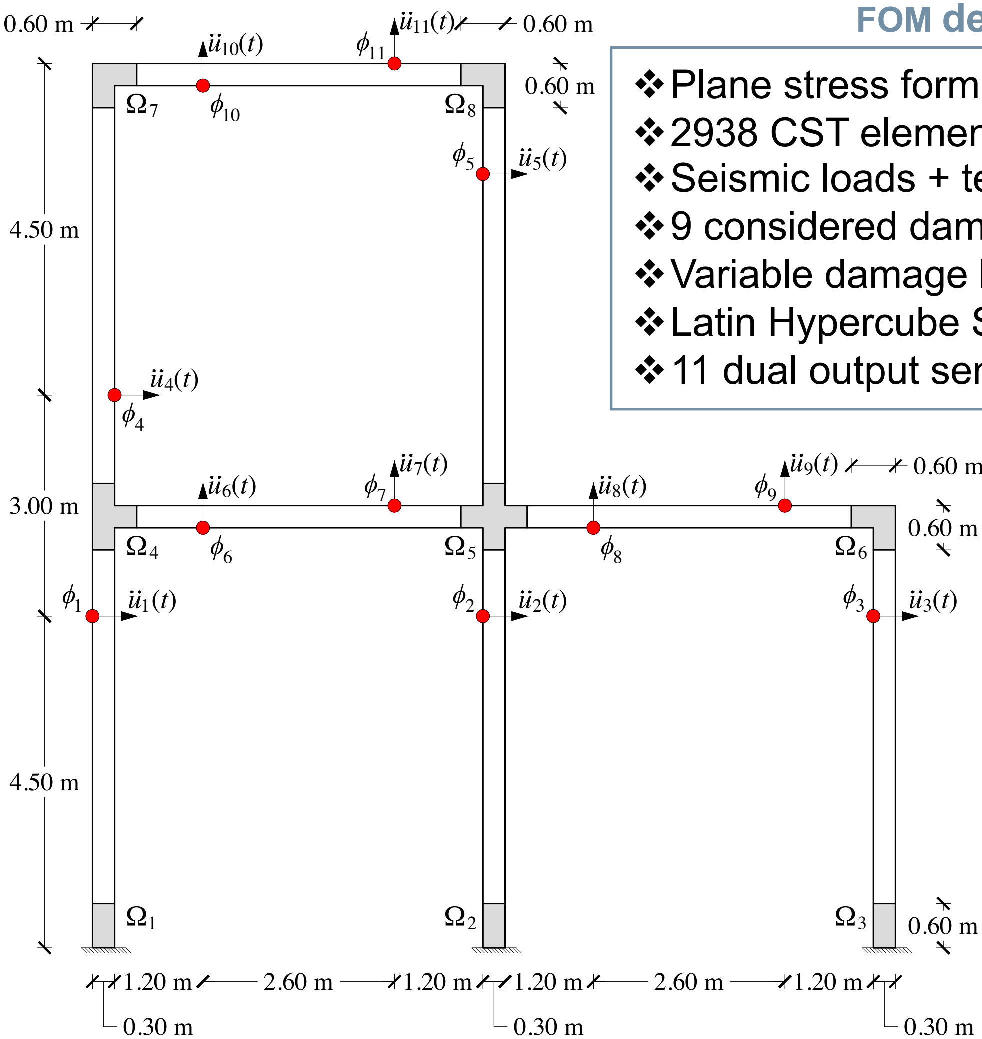
- **Modeling hypoteses:**
  - thermo-elasticity linear theory with a one-way approach;
  - temporal dependence of the thermal field is neglected;
  - damping effects are disregarded;
  - local dependency of the stiffness matrix on the material temperature;
  - damage as a selective reduction (5% ÷ 25%) in stiffness, fixed in time.

- The dataset construction is **accelerated exploiting the ROM:**
  - **The ROM** relies on the **Reduced Basis method;**
  - **The projection bases** are built via **Proper Orthogonal Decomposition.**



A. Quarteroni, A. Manzoni, F. Negri. *Reduced basis methods for partial differential equations*. Springer International Publishing, 2016.

NUMERICAL CASE STUDY

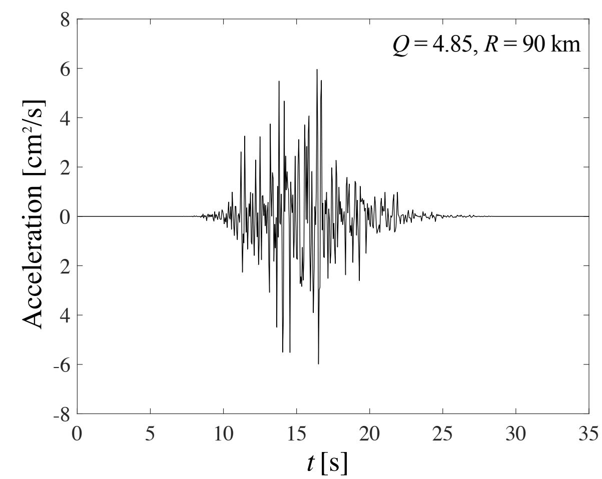


FOM definition

- ❖ Plane stress formulation.
- ❖ 2938 CST elements - 1469 nodes.
- ❖ Seismic loads + temperature profiles.
- ❖ 9 considered damage conditions.
- ❖ Variable damage level (5% ÷ 25%).
- ❖ Latin Hypercube Sampling.
- ❖ 11 dual output sensors (20 Hz).

Low intensity seismic loads

- ❖ Local magnitude (4.8 ÷ 5.3).
- ❖ Epicentral distance (80 ÷ 100)km.
- ❖ Rocky conditions.

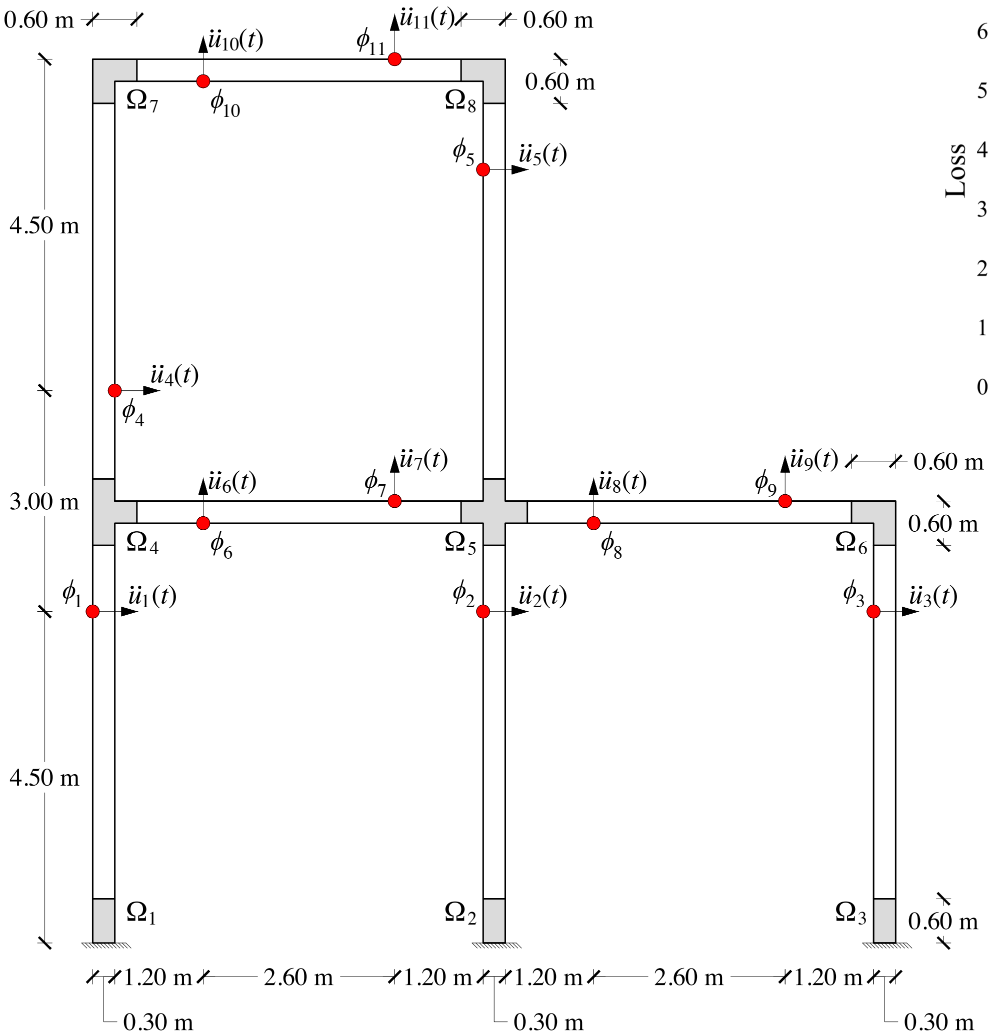


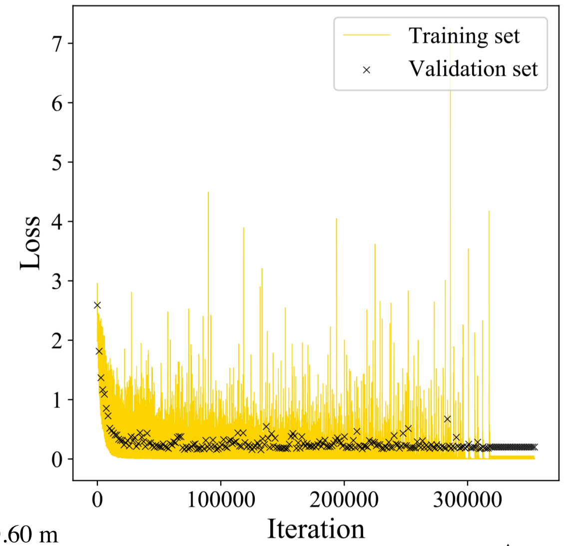
Model Order Reduction

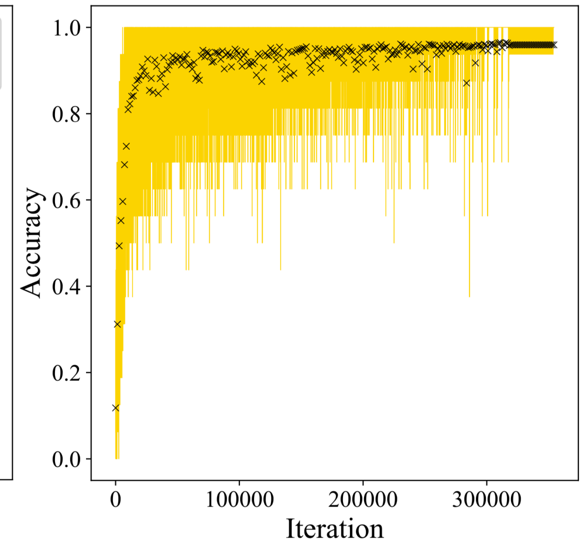
- ❖ Simulations duration = 35 s – (FOM solutions = 380).
- ❖ FOM CPU time = 421 s – ROM CPU time = 4.9 s.
- ❖ Speed-up = 86.
- ❖ ROM dofs = 63 (mechanical) and 28 (thermal).

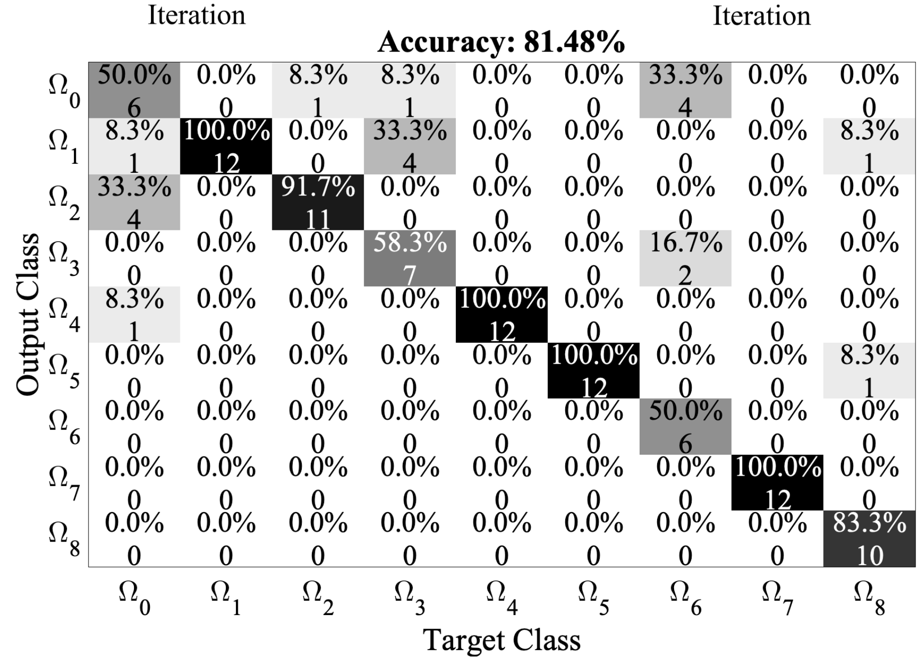
R. Paolucci et al. *Broadband ground motions from 3D physics-based numerical simulations using artificial neural networks*. Bulletin of Seismological Society of America, 108, 2018.
F. Sabetta, A. Pugliese. *Estimation of response spectra and simulation of nonstationary earthquake ground motions*. Bulletin of the Seismological Society of America, 86, 1996.

NUMERICAL CASE STUDY









CONCLUSIONS

- We have proposed a **data-based strategy for SHM** under varying operational and environmental conditions, integrating **model-order reduction and deep learning**.
- The damage localization task has been performed by making use of **vibrational and temperature measurements**.
- A database of **synthetic recordings** has been built offline for a set of predefined damage conditions.
- A reduced order model has been exploited to **accelerate the dataset construction**.
- A DL-based classifier has been adopted to perform the **automatic features extraction** and to relate raw sensor measurments to structural health conditions.
- The classifier has achieved a **global accuracy of about 81.5%,** which is a very good result in the light of **the heterogeneity of the explored conditions** and of the **damage level variability.**

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THANK YOU FOR YOUR ATTENTION!

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Fully coupled problem

- Onset of a volumetric deformation for a temperature variation.
- Onset of internal heat for a variation of the volumetric deformation.

Simplifying hypotheses

- Small strain rate: one-way coulping approach.
- Short monitoring windows: stationary thermal problem.

Algorithm 1 Thermo-Elastic Problem Solution (FOM).

Solve $\mathbf{K}_{\varphi}\boldsymbol{\varphi} = \mathbf{f}_{\varphi} \rightarrow \boldsymbol{\varphi}$

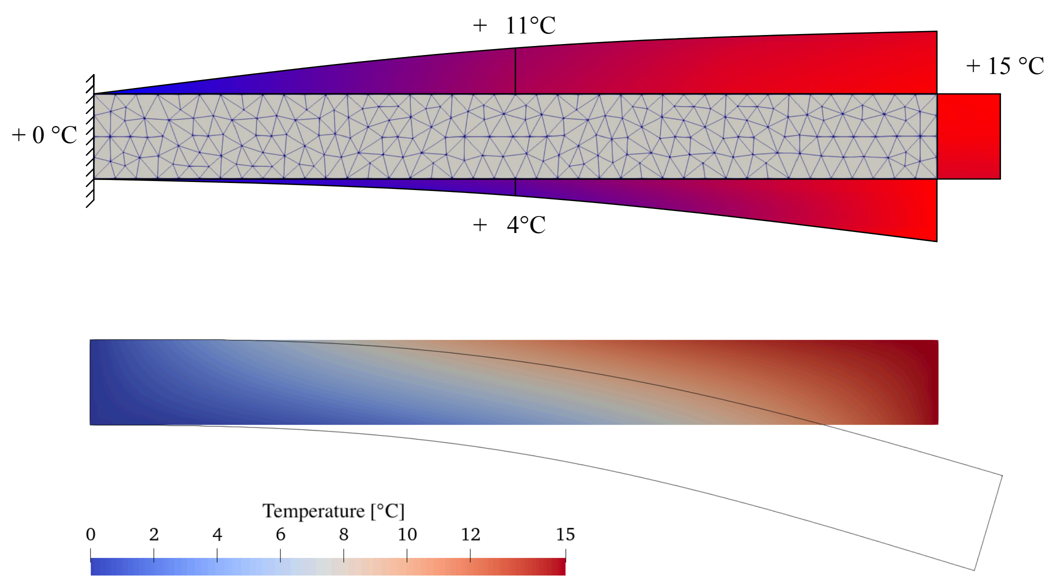
Solve $\mathbf{K}_{v}(\boldsymbol{\varphi})\mathbf{v} = \mathbf{G}_{v}\boldsymbol{\varphi} \rightarrow \mathbf{v}_{\varphi}$

$\mathbf{v}_{\varphi}$ assumed as initial condition: $\mathbf{v}_0 = \mathbf{v}_{\varphi}$

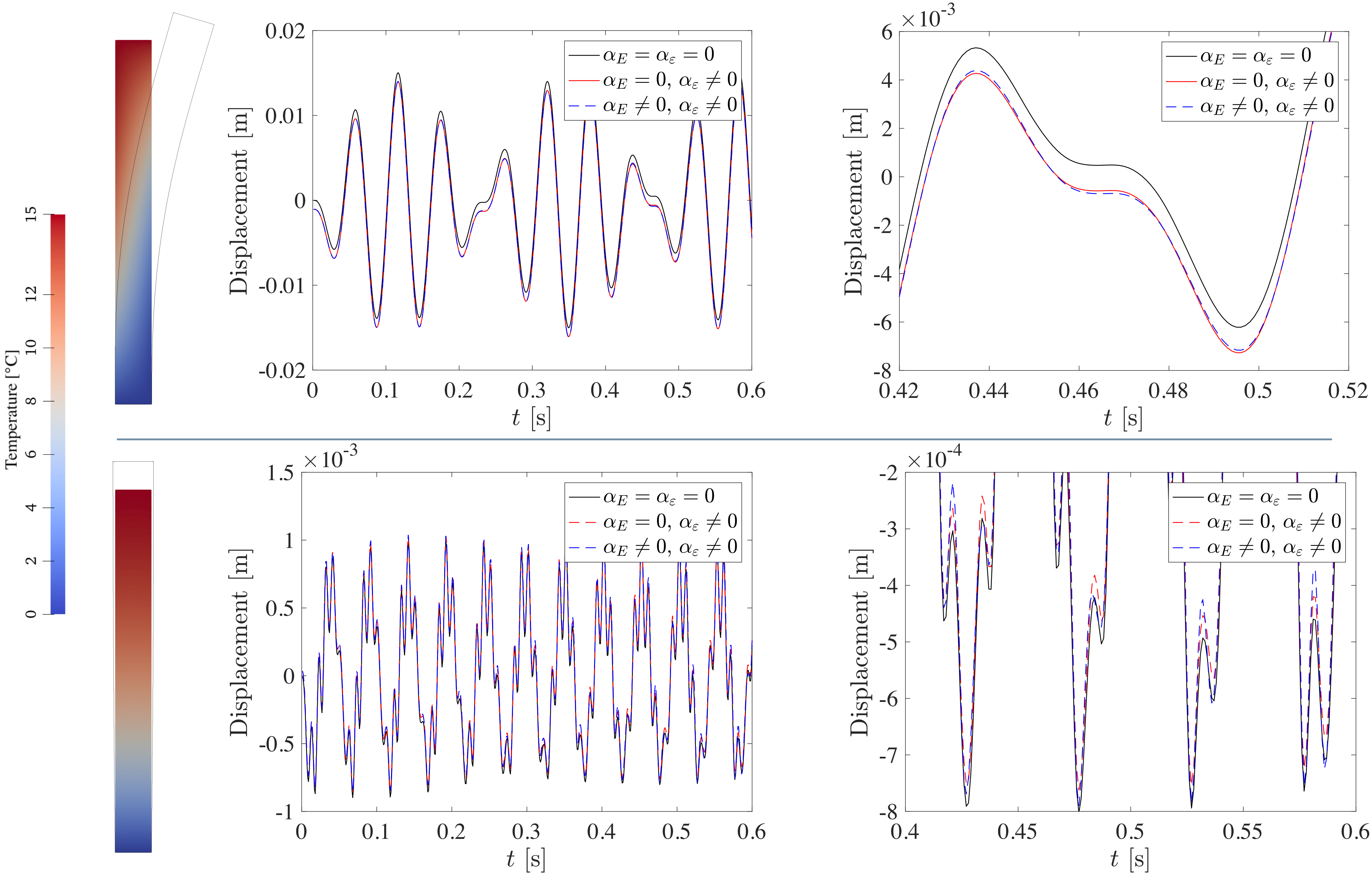
WHILE $t_p < t_{L_S}$ DO

  Solve $\mathbf{M}_v\ddot{\mathbf{v}}(t_p) + \mathbf{K}_v(\boldsymbol{\varphi})\mathbf{v}(t_p) = \mathbf{G}_v\boldsymbol{\varphi} + \mathbf{f}_v(t_p)$

END WHILE



TEMPERATURE EFFECTS ON THE OBSERVED QUANTITIES: TOP-RIGHT TIP VERTICAL DISPLACEMENT



POD BASES CONSTRUCTION ALGORITHM

Algorithm 2 POD bases construction

POD FOR THE COUPLED ELASTO-DYNAMIC PROBLEM

FOR $j = 1, \ldots, \mathfrak{N}$ DO

  Sample $\{\boldsymbol{\eta}_u, \boldsymbol{\eta}_\phi, g\}_j$ via LHS

  Solve $\{\mathbf{K}_\varphi \boldsymbol{\varphi}(\boldsymbol{\eta}_\phi) = \mathbf{f}_\varphi(\boldsymbol{\eta}_\phi)\}_j \rightarrow \boldsymbol{\varphi}(\boldsymbol{\eta}_\phi^j)$

  Call {Algorithm 1} to Solve $\{\mathbf{M}_v \ddot{\mathbf{v}}(t, \boldsymbol{\eta}_u, \boldsymbol{\eta}_\phi, g) + \mathbf{K}_v(\boldsymbol{\eta}_u, \boldsymbol{\varphi}, g)\mathbf{v}(t, \boldsymbol{\eta}_u, \boldsymbol{\eta}_\phi, g) = \ldots$

  $\mathbf{G}_v \boldsymbol{\varphi}(\boldsymbol{\eta}_\phi) + \mathbf{f}_v(t, \boldsymbol{\eta}_u)\}_j \rightarrow \mathbf{v}_j(t_p), \quad p = 1, \ldots, L_S^R$

  Collect $\mathbf{S}_v^j = [\mathbf{v}(t_1, \{\boldsymbol{\eta}_u, \boldsymbol{\eta}_\phi, g\})| \ldots |\mathbf{v}(t_{L_S^R}, \{\boldsymbol{\eta}_u, \boldsymbol{\eta}_\phi, g\})]_j$

  $\mathbf{W}_v^j = \mathrm{POD}_{time}(\mathbf{S}_v^j)$

  IF $j == 1$ THEN

    $\mathbf{W}_v = \mathbf{W}_v^1$

  ELSE

    $\mathbf{S}_p = [\mathbf{W}_v | \mathbf{W}_v^j]$

    $\mathbf{W}_v = \mathrm{POD}_{parameters}(\mathbf{S}_p)$

  END IF

END FOR

POD FOR THE DIFFUSION PROBLEM

Collect $\mathbf{S}_\varphi = [\boldsymbol{\varphi}(\boldsymbol{\eta}_\phi^1)| \ldots |\boldsymbol{\varphi}(\boldsymbol{\eta}_\phi^{\mathfrak{N}})]$

$\mathbf{W}_\varphi = \mathrm{POD}(\mathbf{S}_\varphi)$

Reduced solution algorithm

Algorithm 3 Thermo-Elastic Problem Solution (ROM).

Compute $\mathbf{K}_\varphi^R = \mathbf{W}_\varphi^\top \mathbf{K}_\varphi \mathbf{W}_\varphi, \quad \mathbf{f}_\varphi^R = \mathbf{W}_\varphi^\top \mathbf{f}_\varphi$

Solve $\mathbf{K}_\varphi^R \boldsymbol{\varphi}^R = \mathbf{f}_\varphi^R \to \boldsymbol{\varphi}^R$

Compute $\boldsymbol{\varphi} = \mathbf{W}_\varphi \boldsymbol{\varphi}^R$

Compute $\mathbf{M}_v^R = \mathbf{W}_\varphi^\top \mathbf{M}_v \mathbf{W}_\varphi, \quad \mathbf{G}_v^R = \mathbf{W}_\varphi^\top \mathbf{G}_v, \quad \mathbf{K}_v^R = \mathbf{W}_\varphi^\top \mathbf{K}_v(\boldsymbol{\varphi}) \mathbf{W}_\varphi, \quad \mathbf{f}_v^R = \mathbf{W}_\varphi^\top \mathbf{f}_v$

Solve $\mathbf{K}_v^R(\boldsymbol{\varphi})\mathbf{v}^R = \mathbf{G}_v^R \boldsymbol{\varphi} \to \mathbf{v}_\varphi^R$

$\mathbf{v}_0^R = \mathbf{v}_\varphi^R$

WHILE $t_p < t_{L_S}$ DO

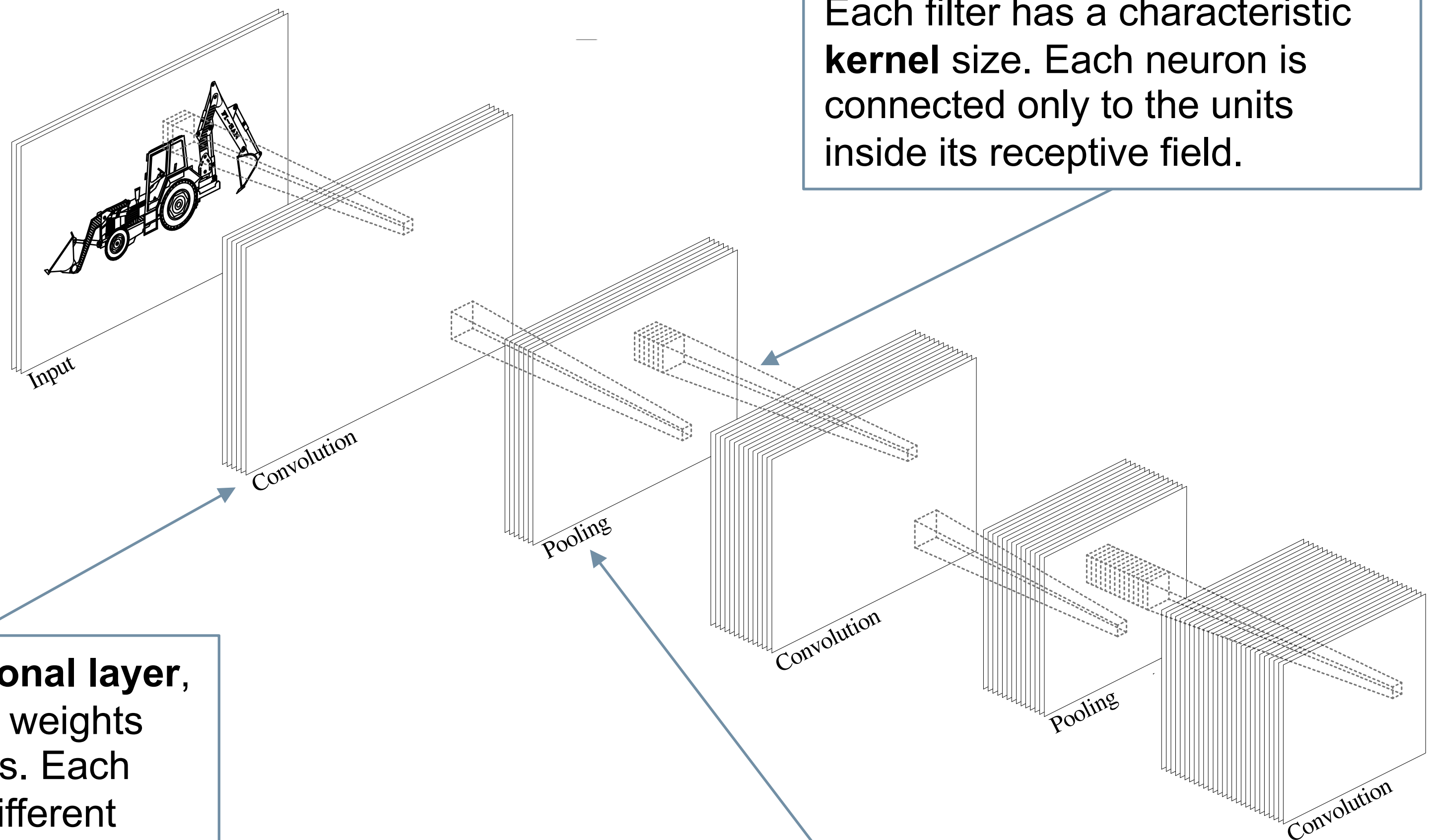
    Solve $\mathbf{M}_v^R \ddot{\mathbf{v}}^R(t_p) + \mathbf{K}_v^R(\boldsymbol{\varphi})\mathbf{v}^R(t_p) = \mathbf{G}_v^R \boldsymbol{\varphi} + \mathbf{f}_v^R(t_p)$

    Compute $\mathbf{v}(t_p) = \mathbf{W}_\varphi \mathbf{v}^R(t_p)$

END WHILE

Convolutional Neural Network (CNN)

Inspired by the visual cortex and typically used in computer vision.



Each filter has a characteristic **kernel** size. Each neuron is connected only to the units inside its receptive field.

In a convolutional layer, the connection weights are called filters. Each layer applies different kernel filters to its inputs, thus its output consists of multiple feature maps.

The pooling layer operates a dimensionality reduction of the data by subsampling its inputs through average or maximum functions.