Earthquake-Induced Damage Estimation in Structural Systems using Parametric Physics-Based Reduced-Order Models

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Earthquake induced damage estimation in structural systems using parametric physics-based Reduced-Order Models (ROMs)

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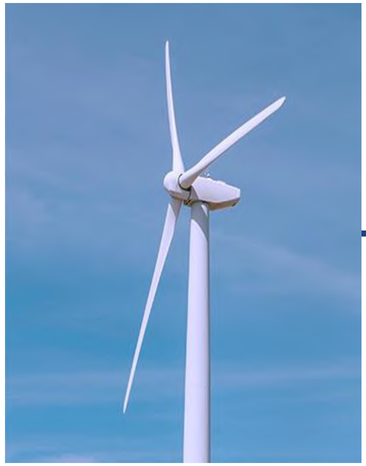
Problem Statement

Robust digital virtualization of nonlinear dynamical systems



Reference system
(real-life)

High Fidelity Model
(finite element model)

HFM features:

Complex dynamics

Nonlinear behaviour

Parametric dependencies on:

- *Geometric features*
- *Material properties*
- *EOPs:*
  - *Environmental conditions*
  - *Operational conditions*
- *Excitation*

Low-order representation that:

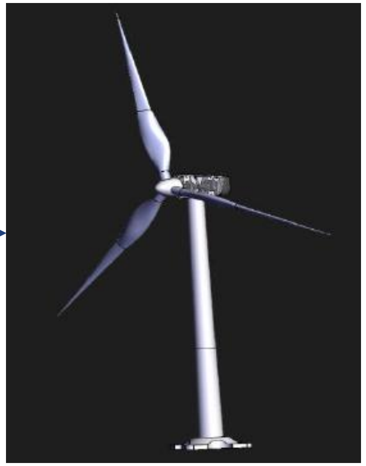
Captures underlying dynamics

Reproduces physical behaviour

Retains parametric dependencies

Computationally efficient

parametric Reduced Order Model
(low-order, equivalent model)



Virtual representation

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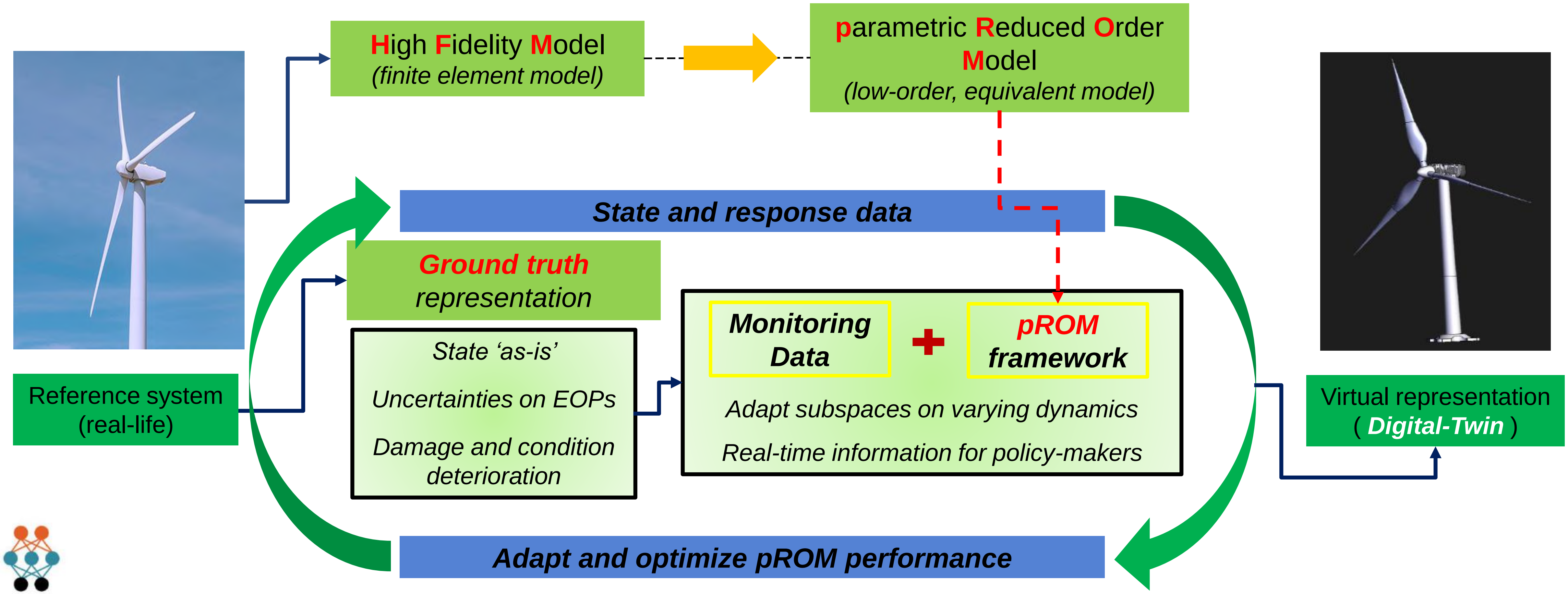
Problem Statement

Condition deterioration or damage during operation

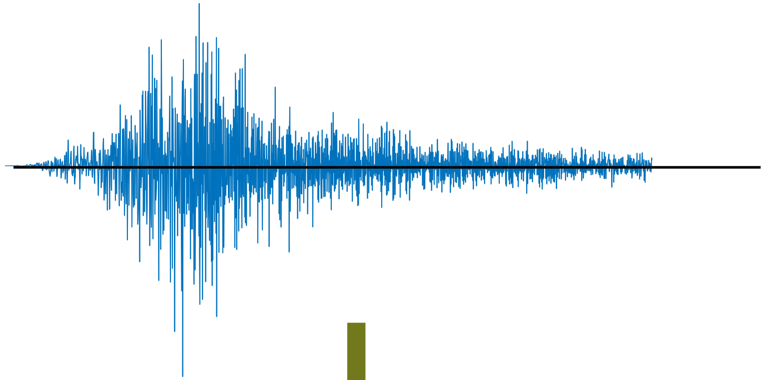


Approach conceptualization

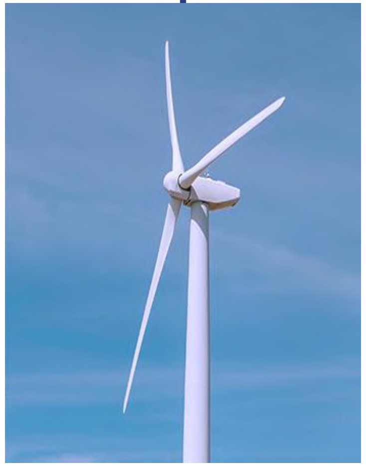
Parametric ROM (pROM) as forward simulator

High **F**idelity **M**odel
(finite element model)

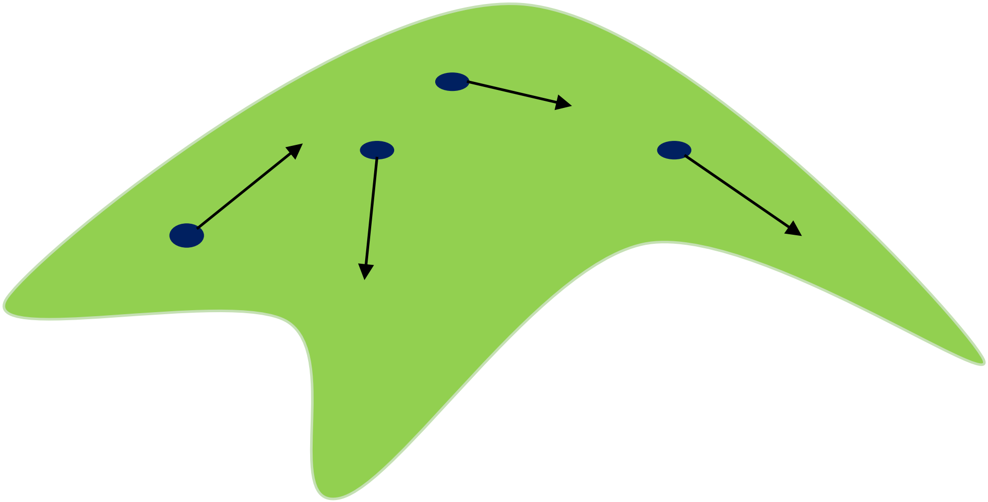
Evaluate training instances
of dynamic structural response



Reference system
(real-life)



Approximate solution manifold S
based on dominant components



Physical Interpretation:
*Dynamic response under any input state spans low-dimensional subspace approximation of **S***

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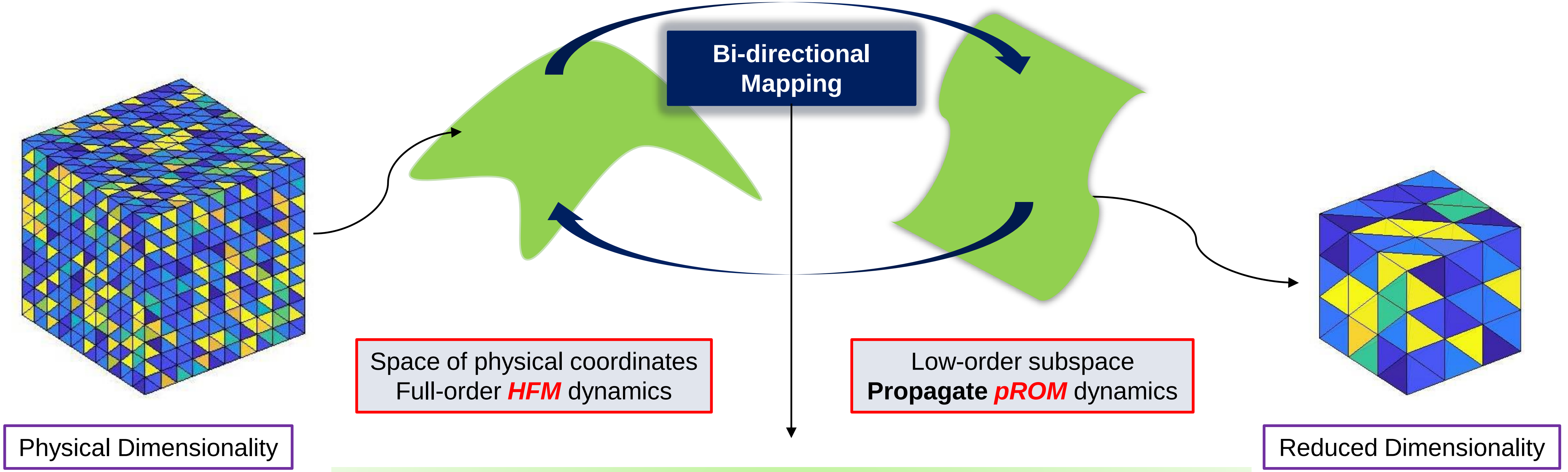
Approach conceptualization

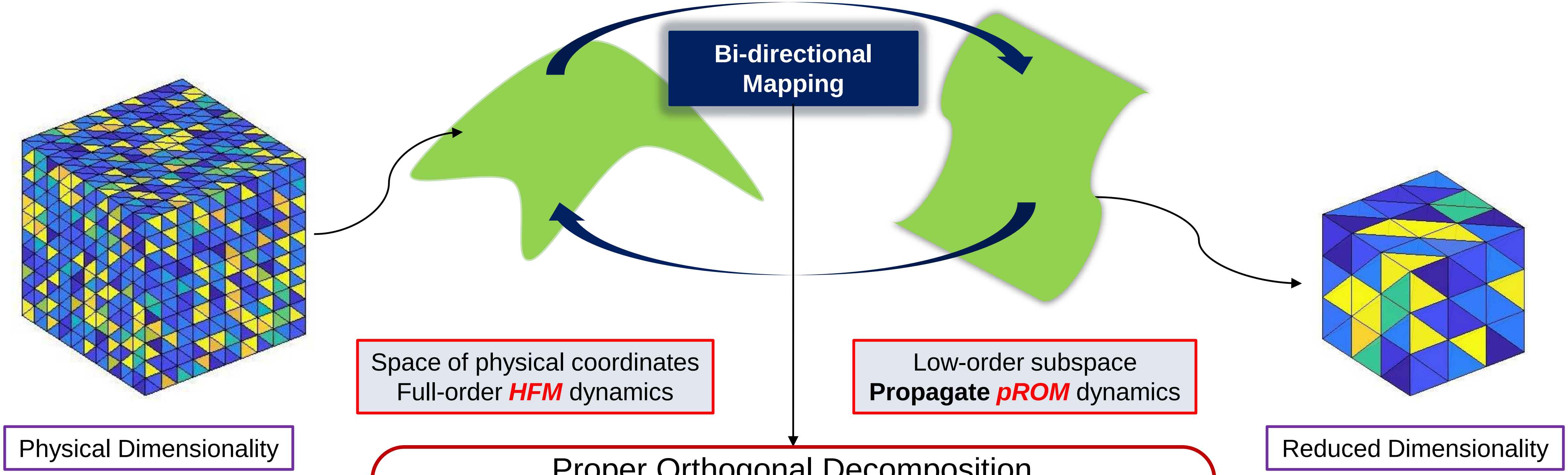
Projection-based pROM as forward simulator



- ***Captures high fidelity dynamics***
- ***Approximates time domain quantities***
- ***Retains parametric dependencies***
- ***Inverse mapping exists***
- ***Propagates dynamics in reduced space => Efficiency***

Approach conceptualization

Projection-based pROM as forward simulator



Proper Orthogonal Decomposition

$$\mathbf{u}(t) = \mathbf{V}(\mathbf{p})\mathbf{u}_{\mathrm{r}}(t) \qquad \mathbf{U} \equiv [\mathbf{u}(t_1)...\mathbf{u}(t_N)] = \mathbf{W}\boldsymbol{\Sigma}\mathbf{R}^T$$

$$\mathbf{V} \equiv \mathbf{W}_k = \mathbf{W}(:, 1 : \mathrm{k})$$

Approach conceptualization

Adaptive pROM for robust Structural Health Monitoring

(Initial) parametric ROM framework

- ***Projection-based*** *approach relying on* ***POD subspaces***
- ***Propagates*** *dynamics forward in time in reduced coordinates*
- *Utilizes* ***local ROMs*** *through* ***clustering to retain dependencies*** *throughout domain of operation*

Earthquake induced damage / System deterioration

The pROM is no longer able to perform estimation tasks accurately

Subspaces on training set do not sufficiently capture occurring phenomena

=> Performance bottleneck

Adaptivity in a pROM context

Condition indicator to highlight failure of ROM on the fly

Update subspace / Approximate *deformation modes* anew

=> Adaptive pROM

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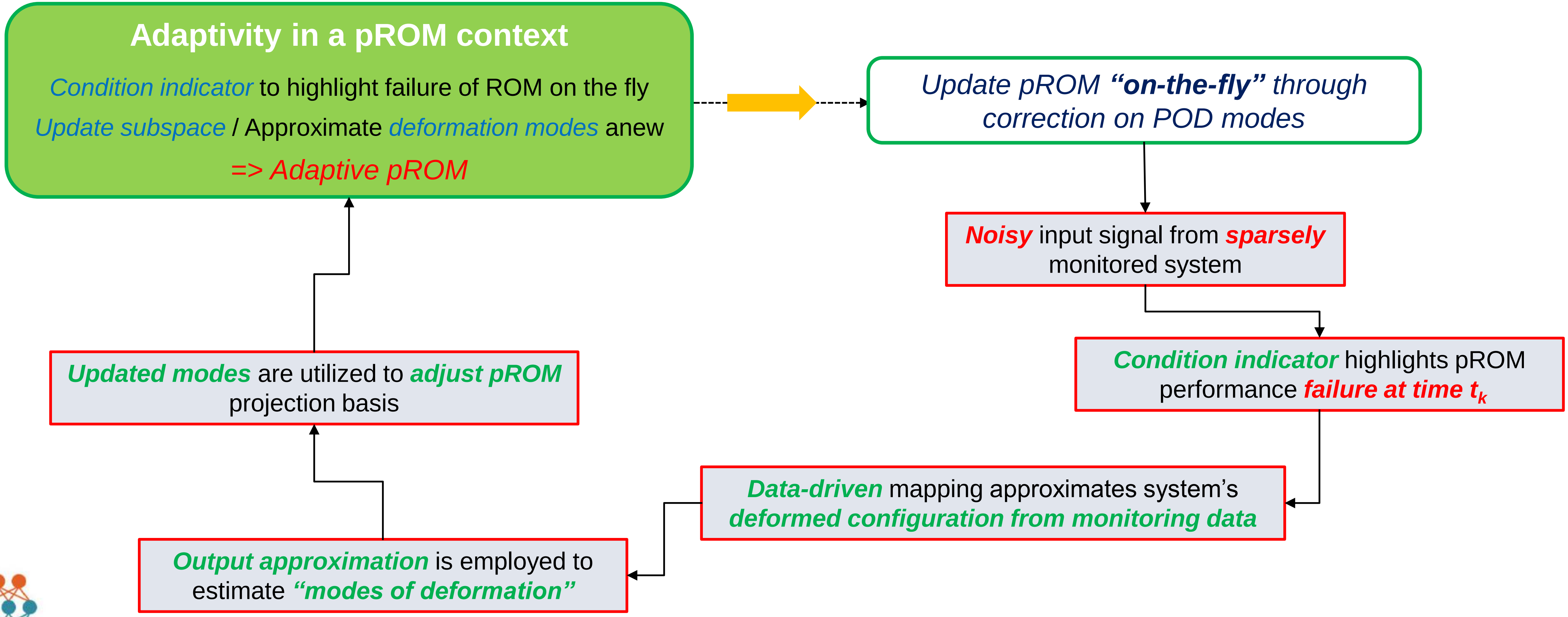
Approach conceptualization

Adaptivity through data assimilation



Approach conceptualization

Adaptive pROM framework based on data assimilation

Offline / Training Strategy:

✓ Derive initial ***pROM as forward simulator*** :

Examples:

- ***Initial linear state*** *and* ***nonlinearities*** *during operation* ***to represent damage***
- ***Initial nonlinear state*** *and* ***deterioration effects*** during operation

✓ Assemble ***Damage Indicator*** :

- ***Deterministic nature*** based on response comparison metrics
- Relies on ***limited nodal measurements***
- Includes input noise / exploit ***noise statistics to define activation threshold***

✓ ***Gaussian Process Regression (GPR)*** trained on ***residual response***:

- GPR ***trained on pool of snapshots***, without compromising efficiency

Examples:

- GPR trained on certain parametric states representing damage

Online / During Operation:

- ***Monitor residual response*** between pROM and monitoring data
- ***If indicator signals*** “ROM Performance Deteriorates”:
  - ✓ Employ GPR estimation to ***reconstruct full residual state***
  - ✓ ***Enrichment mode*** = ***pROM approximation + GPR residual***
  - ✓ ***Enrich pROM*** by using corrected modes in Basis

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Implementation details

Configurations and scenarios

Cantilever Beam Case Study

- Stochastic ***ground motion excitation***
- Parametrized Boundary => ***Nonlinear rotational spring***
- ***Limited number*** of nodes monitored

Damage Scenario:

- ✓ Derive ***ROM based on "design"*** case study
- ✓ Induce **damage** by ***activating parametric boundary***
- ✓ Use ***indicator to detect*** failure
- ✓ Employ ***GPR-based scheme*** to assemble deformed modes
- ✓ ***Refine*** POD-Basis

Hysteretic spring model

- ***Total restoring force:***

$$\mathbf{R} = \mathbf{R}_{linear} + \mathbf{R}_{hysteretic} = \alpha k \mathbf{u} + (1-\alpha) k \mathbf{z}$$

- ***Bouc-Wen equation with degradation/deterioration effects:***

$$\dot{\mathbf{z}} = \frac{A\dot{\mathbf{u}} - \nu(t)(\beta|\dot{\mathbf{u}}|\mathbf{z}|\mathbf{z}|^{w-1} - \gamma\dot{\mathbf{u}}|\mathbf{z}|^{w})}{\eta(t)}$$

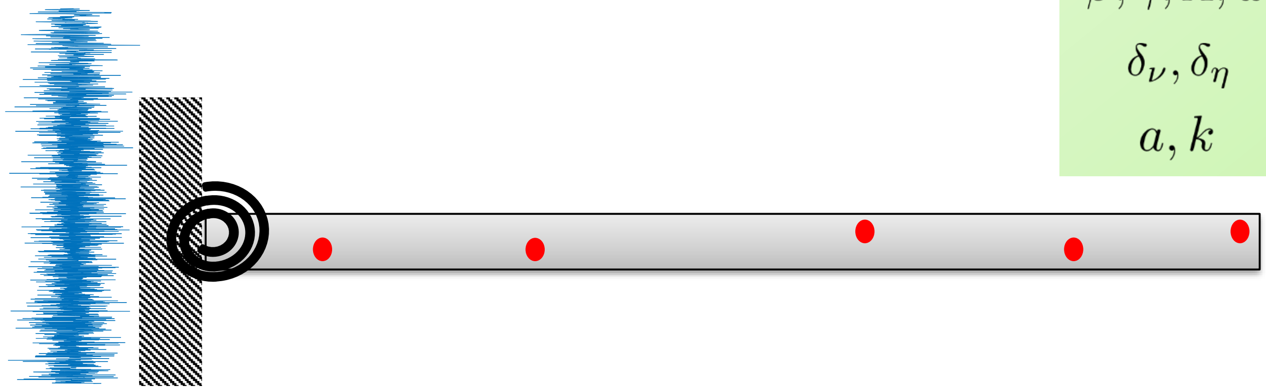
$$\nu(t) = 1.0 + \delta_\nu \epsilon(t), \quad \eta(t) = 1.0 + \delta_\eta \epsilon(t), \quad \epsilon(t) = \int_0^t \mathbf{z}\dot{\mathbf{u}}\delta t$$

Characteristics of the Bouc-Wen links:

β, γ, A, w : Control smoothness and shape of *hysteresis*

δ_ν, δ_η : *Degradation/Deterioration effects*

a, k : *Linear/Hysteretic contribution weighting*



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δ_ν, δ_η : *Degradation/Deterioration* effects

a, k : *Linear/Hysteretic* contribution weighting

Scenario B:

- ***Initial*** "design" case study is ***nonlinear***
- ***Damage*** is represented through ***degradation / deterioration*** effects during ***operation***

Scenario A:

- ***Initial*** "design" case study is ***linear***
- ***Nonlinear spring*** is activated during ***operation***

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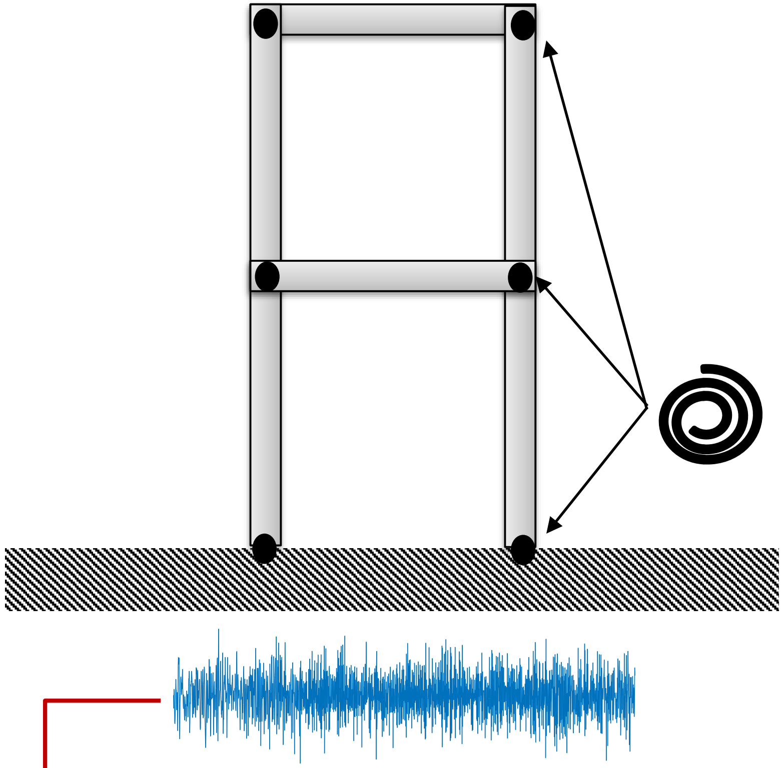
Implementation details
Configurations and scenarios

Plane Frame Case Study

- Stochastic ***parametrized*** ground motion ***excitation (Amplitude)***
- ***Nonlinear*** parametric rotational ***spring on all nodal connections***
- ***Limited number*** of nodes monitored

Damage Scenario:

- ✓ Derive ***ROM based on "design"*** case study
- ✓ Induce **damage** by ***activating parametric springs***
- ✓ Use ***indicator to detect*** failure
- ✓ Employ ***GPR-based scheme*** to assemble deformed modes
- ✓ ***Refine*** POD-Basis



Scenario C*:*

- ***Initial*** "design" case study is ***linear***
- ***Nonlinear spring*** is activated during ***operation***
- Evaluation earthquake not included in training set

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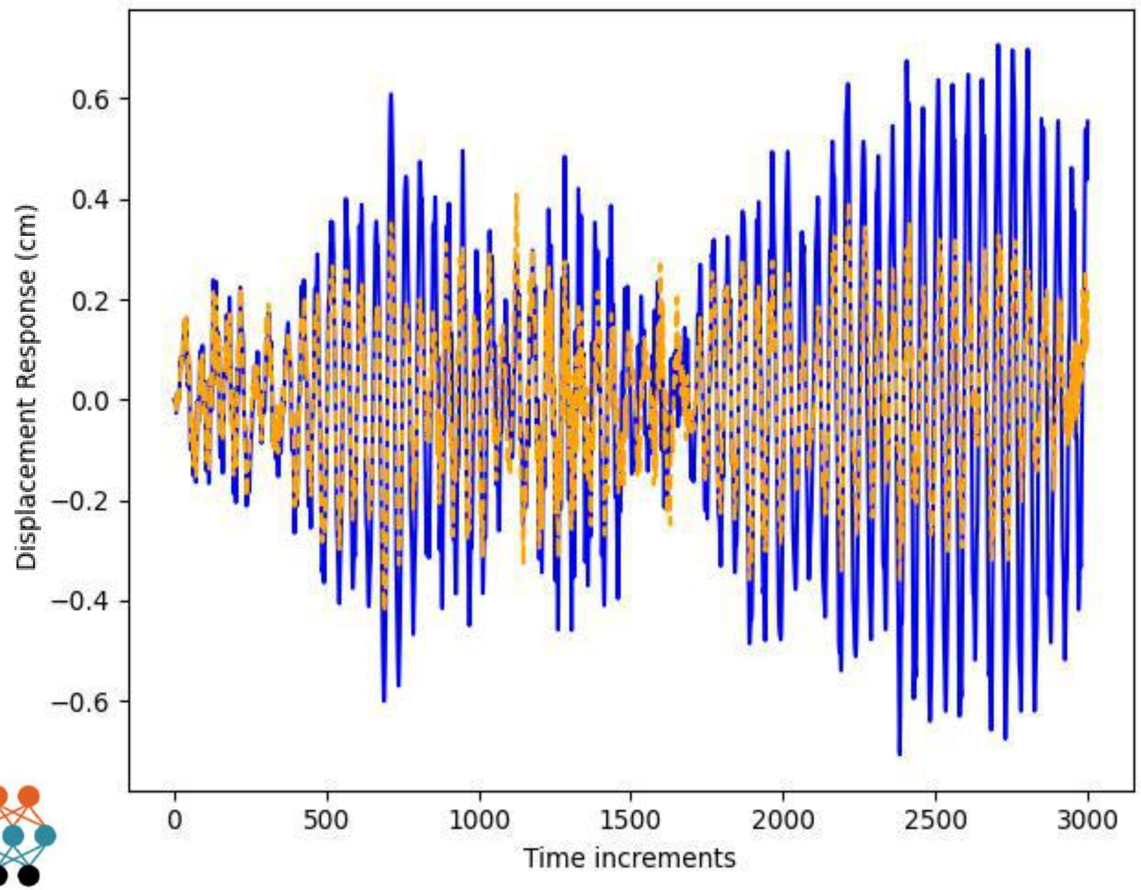
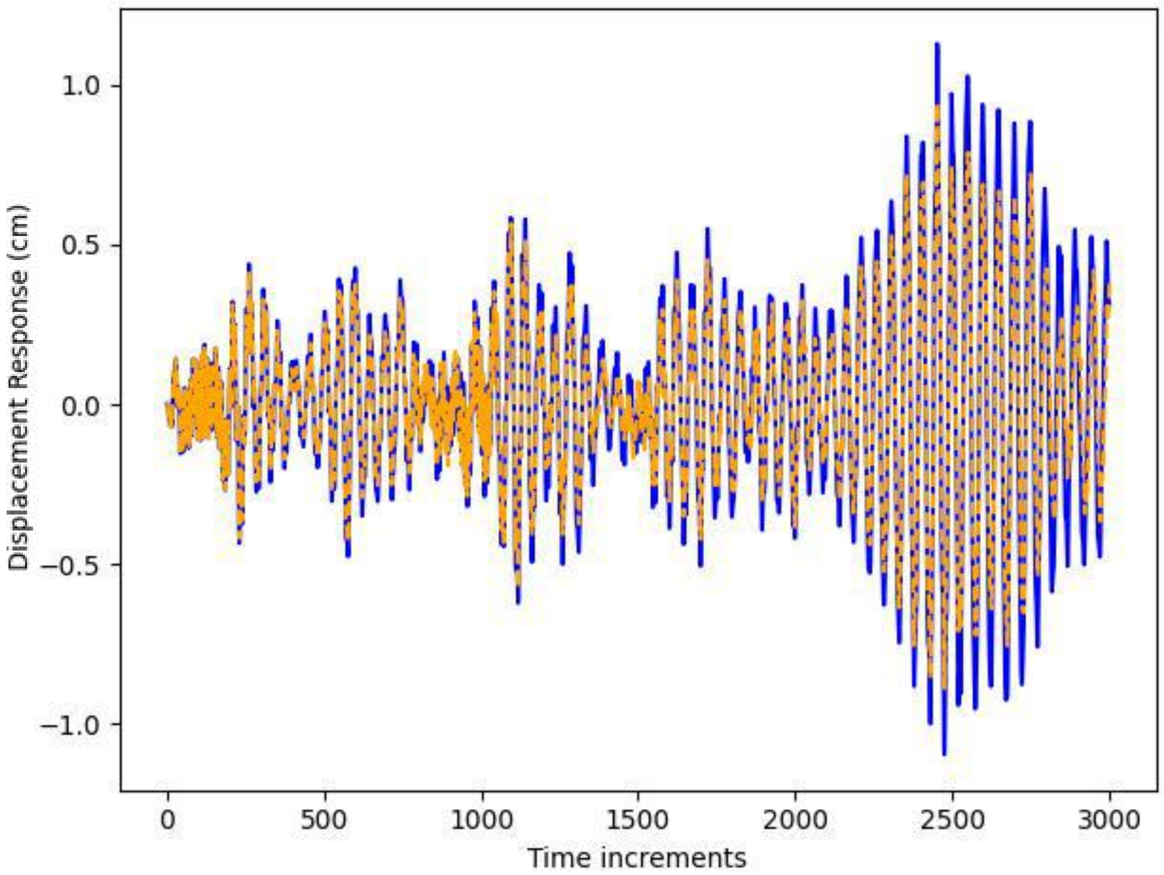
Implementation details
Configurations and scenarios

Linear vs Nonlinear response examples for ***different Bouc-Wen activation parameters***





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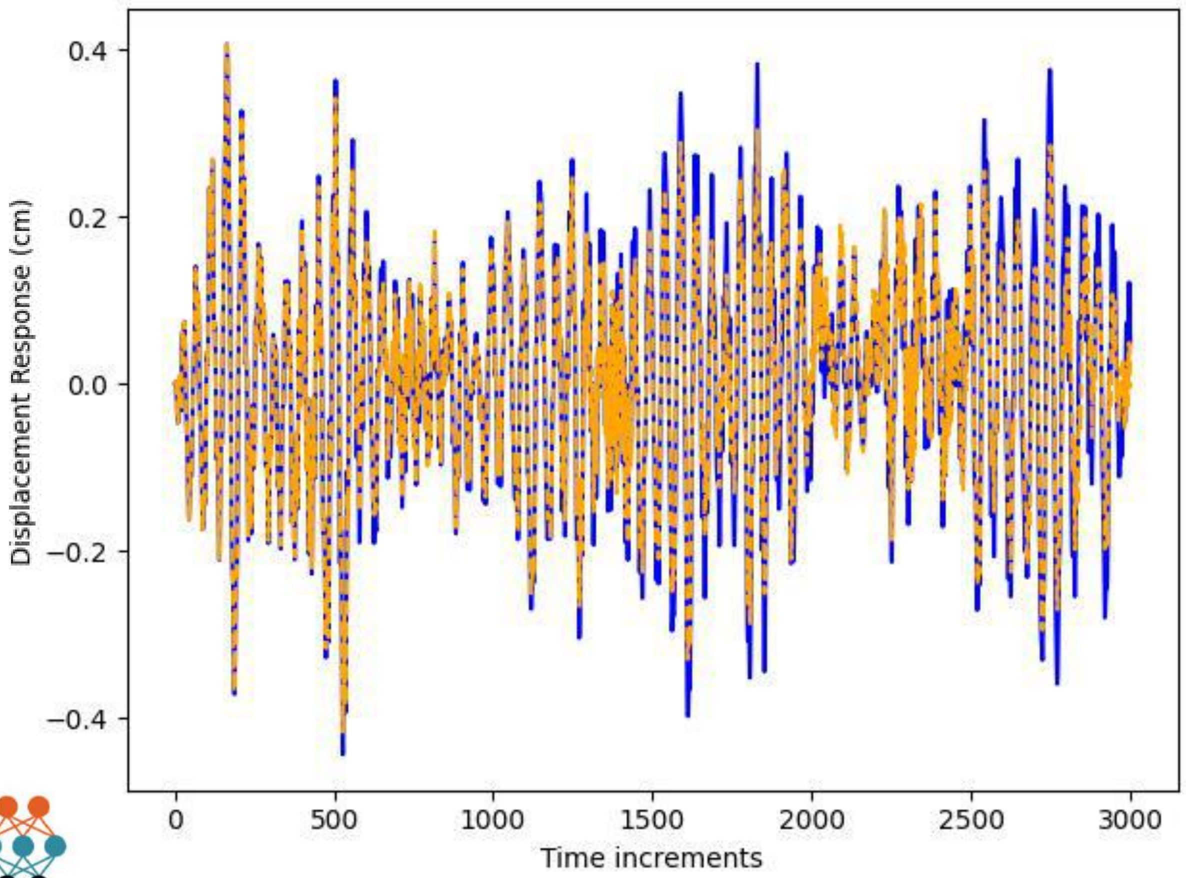
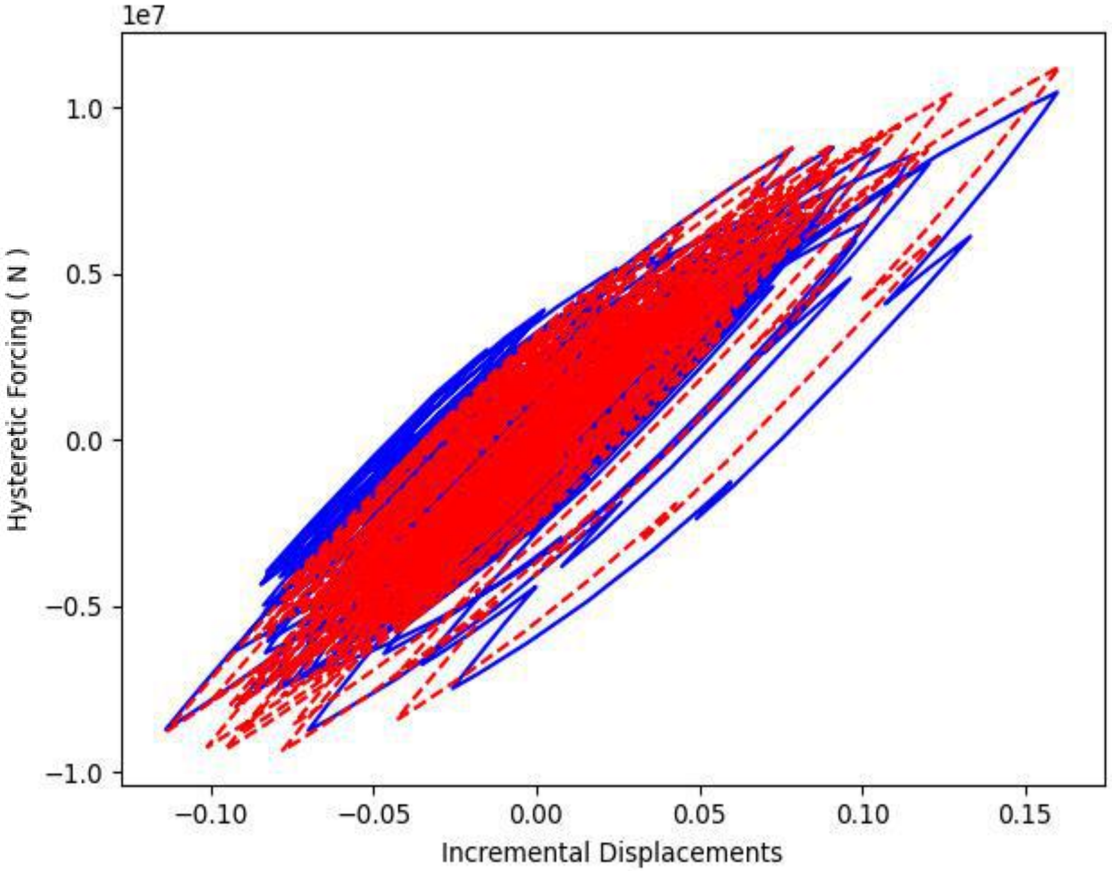
Implementation details

Configurations and scenarios

Response examples with ***Bouc-Wen degradation phenomena*** during operation





Implementation details

Damage indicator and GPR-scheme

Damage Indicator

- Deterministic nature based on response comparison metrics
  => Mahalanobis distance (MD) measure
- Relies on limited nodal measurements (5-10% nodal output measured)
- Includes input noise (3%) / exploit noise statistics to define activation threshold
  => Alert threshold from Chi-Square distribution (0.01% significance level)

Gaussian Process Regression (GPR)

- Trained based on ***residual responses*** between monitoring data and pROM
- GPR ***trained on pool of snapshots***, without compromising online efficiency
- ***Input***: Response information from monitoring channels
  Output: Additive correction on full coordinate space
- Leverage ***local*** and ***physical degree-of-freedom correlations***
- ***Software***: ***gpytorch*** implementation with MultitaskGPModel and RBFKernel()

Measurement Data $\mathbf{d}_k \in \mathbb{R}^{n_d}$

Vector of random values $\mathbf{r}_k \in \mathbb{R}^{n_d}$

St. Dev. of measurement signals $\sigma_\delta \in \mathbb{R}^{n_d \times n_d}$

Noise level δ

Noisy measurement data

$$\tilde{\mathbf{d}}_k = \mathbf{d}_k + \delta \sigma_d \mathbf{r}_k$$

Damage Indicator

$Input \in \mathrm{R}^{N_{channels} * 2 \times 1}$

Response on monitoring channels (displacements & rotations)

Output => Performance failure alert signal

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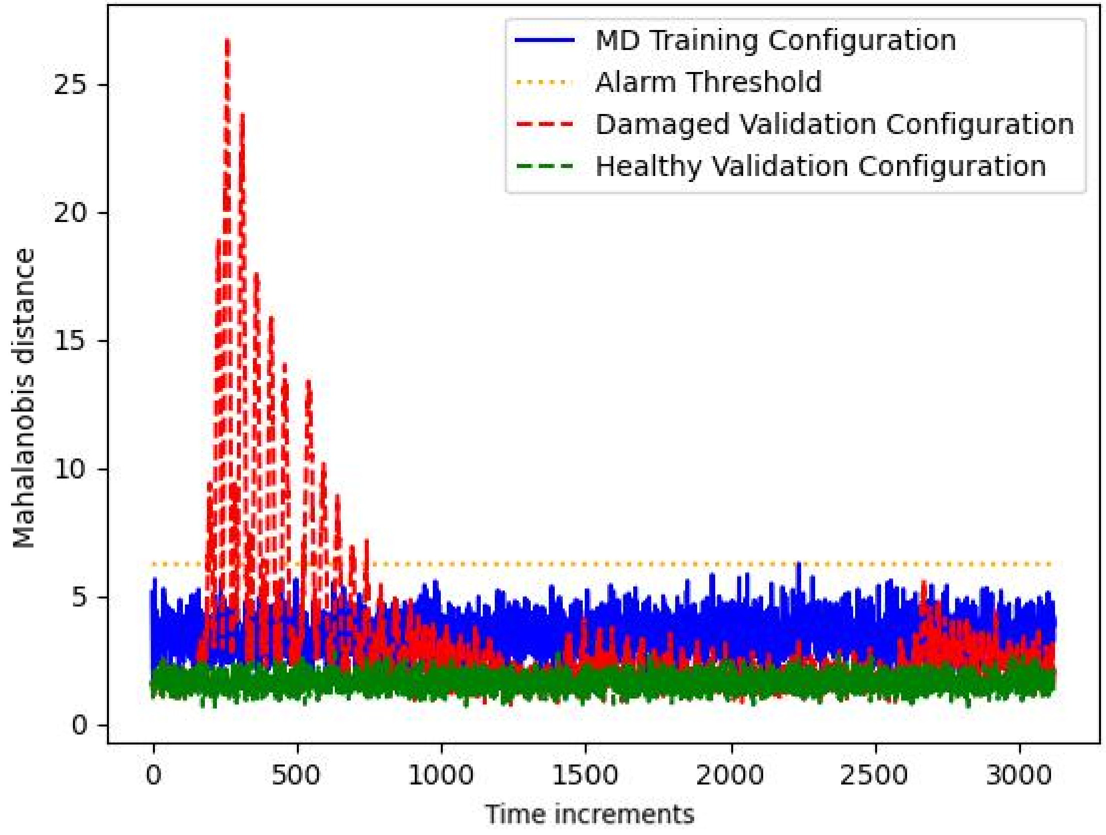
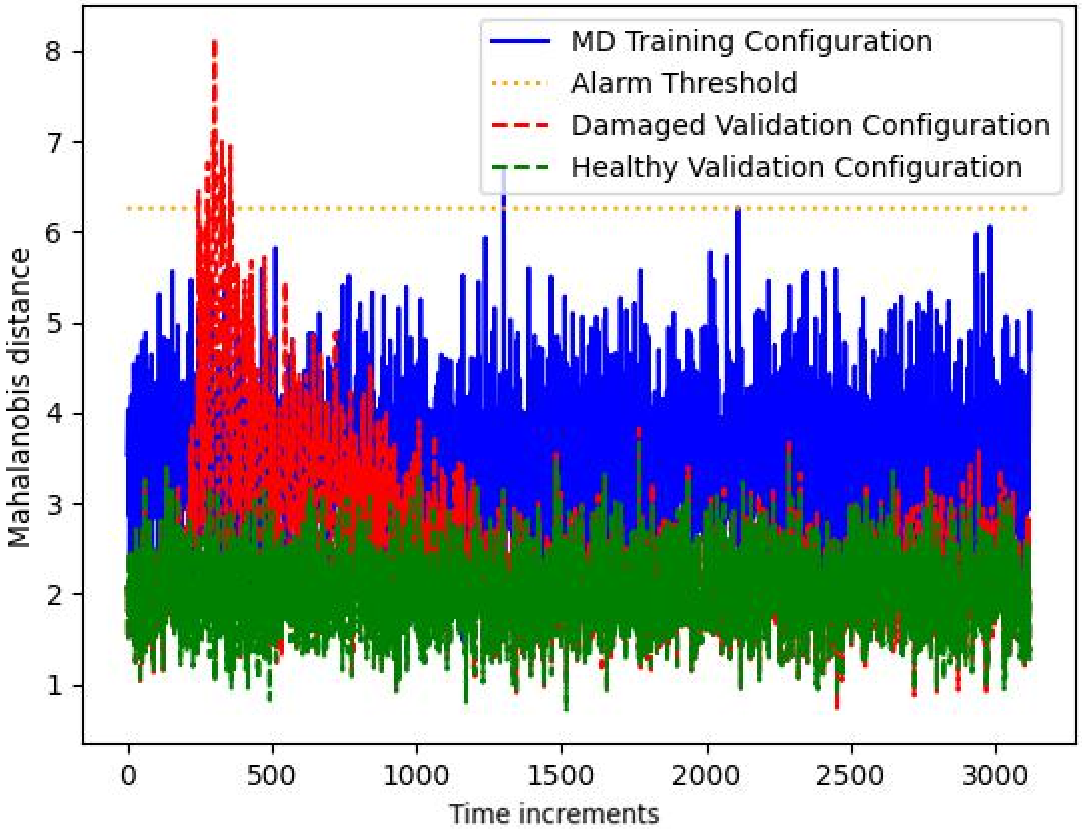
Implementation details

Damage indicator and GPR-scheme





Linear vs Nonlinear
response example (***Scenario A***)

Bouc-Wen degradation phenomena
during operation (***Scenario B***)

Implementation details

Damage indicator and GPR-scheme

Gaussian Process Regression (GPR)

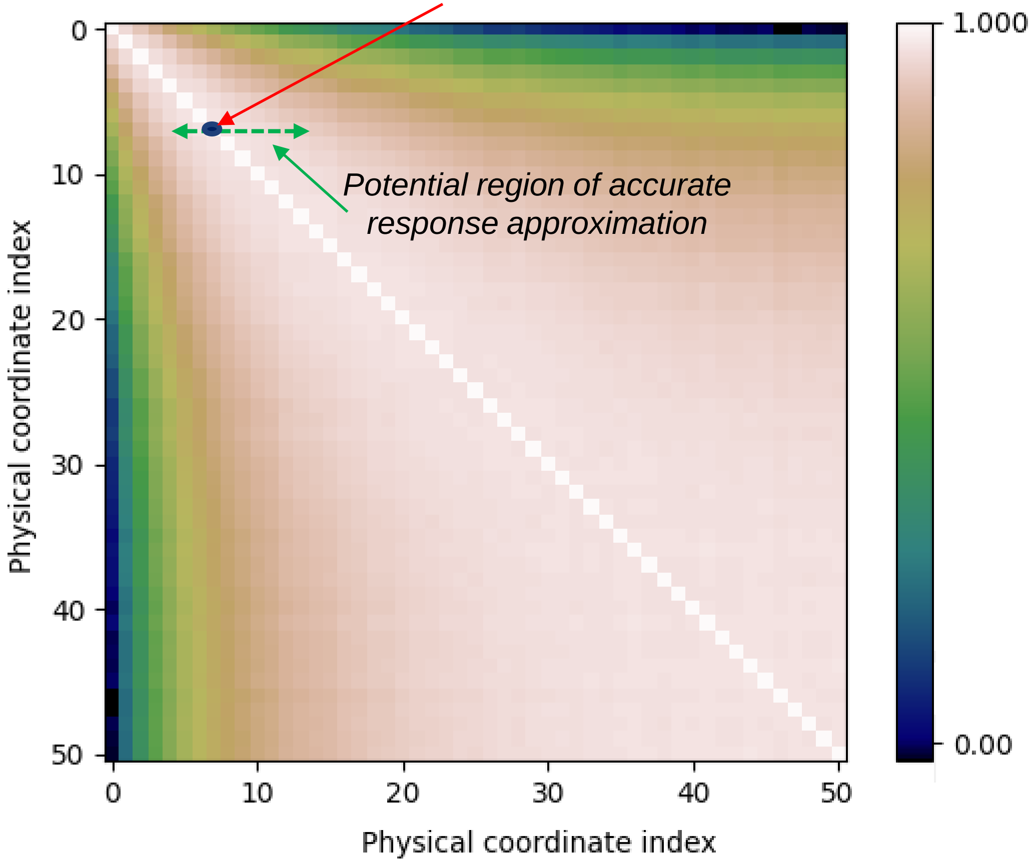
- Trained based on ***residual*** between monitoring data and pROM
- ***Input*** : Response information in monitoring channels (displacements & rotations)
  Input = True response - pROM estimation (monitored coordinates)
- ***Output***: Response approximation through additive correction on full coordinate space
  Output = True response - pROM estimation (all coordinates)
  => pROM **Basis Enrichment** mode = ***pROM approximation*** **+** ***GPR residual***
- GPR trained on pool of snapshots, without compromising online efficiency
- Leverage ***local*** and ***physical degree-of-freedom correlations***

✓ Assemble indirect ***correlation*** matrices between ***response in each physical coordinate*** / degree-of-freedom

✓ Leverage correlations to ***define output window*** for each monitored input channel

✓ ***Overlapping*** to ensure quality of approximation

Example correlation pattern



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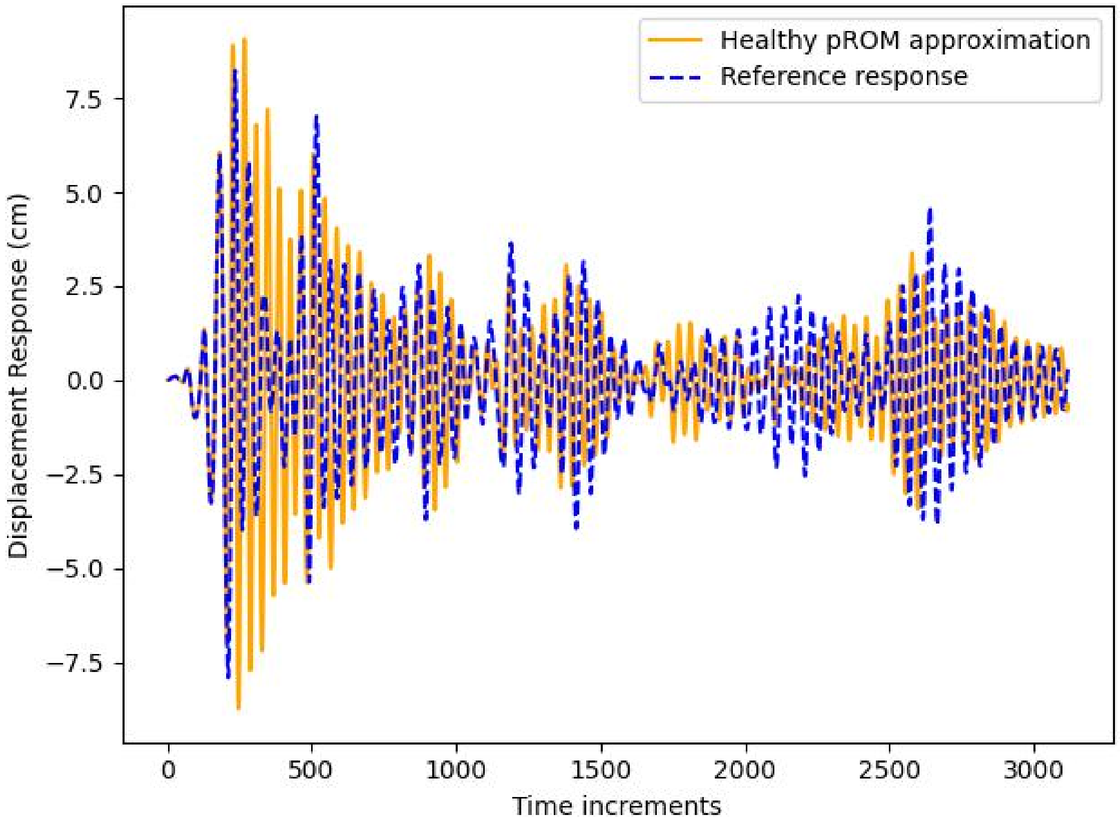
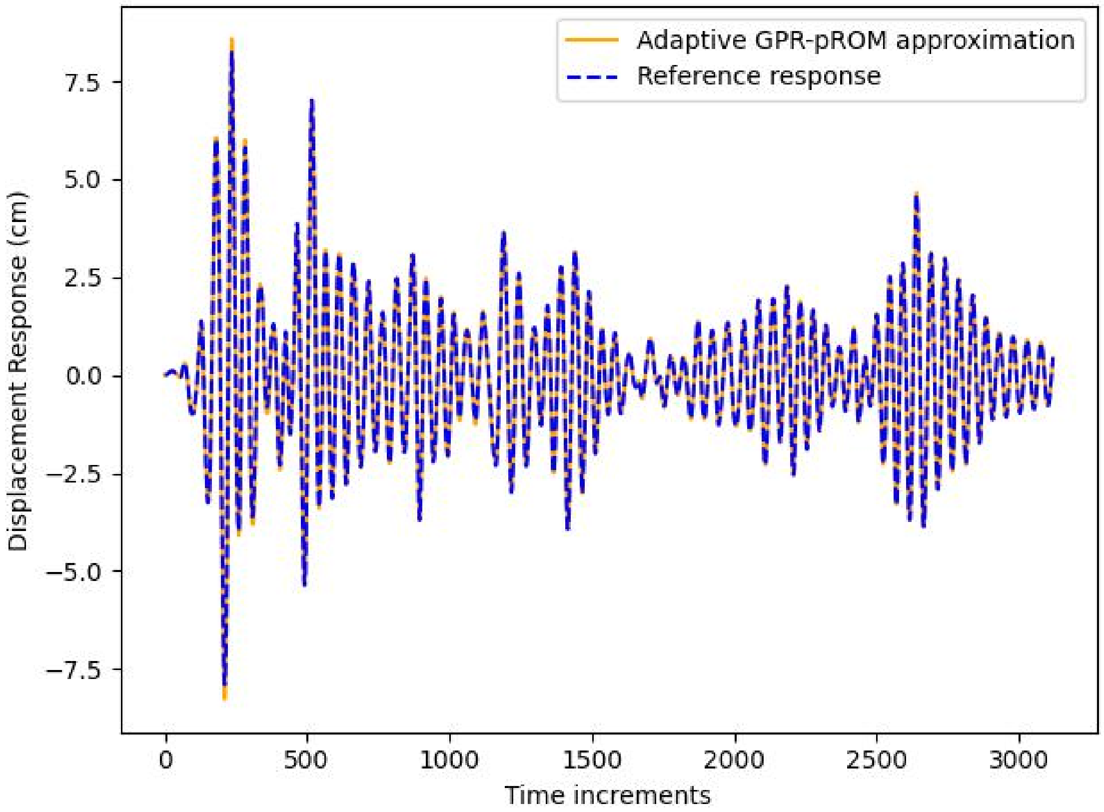
Case studies

Accuracy performance of the framework



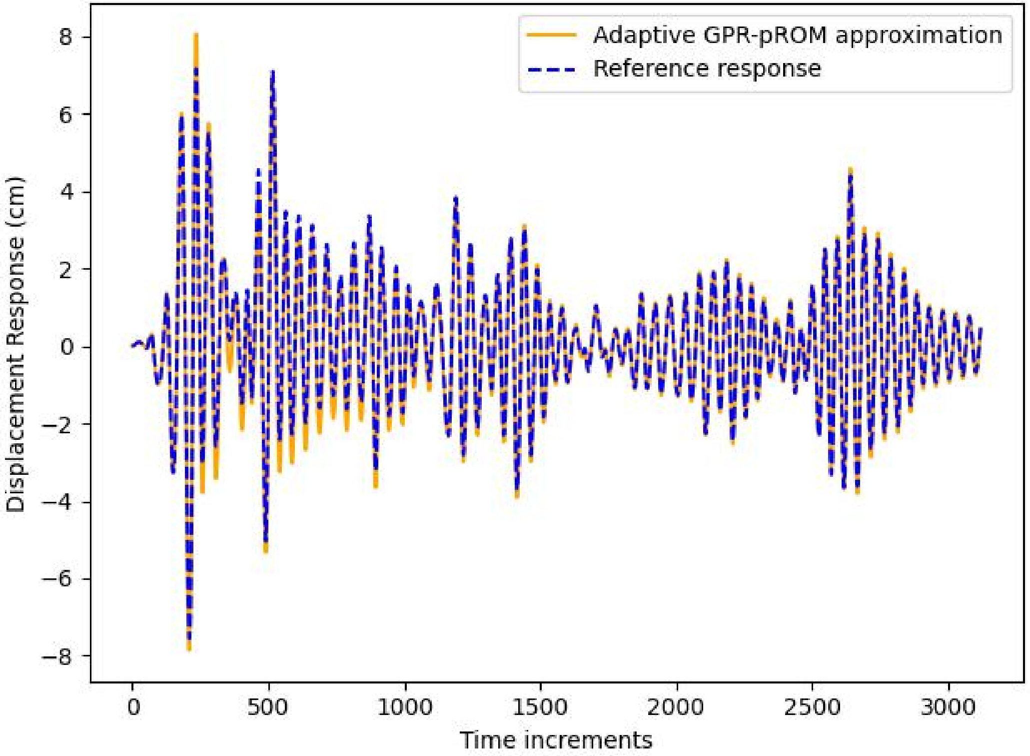
Healthy pROM uses
initial linear Basis (***Scenario A***)

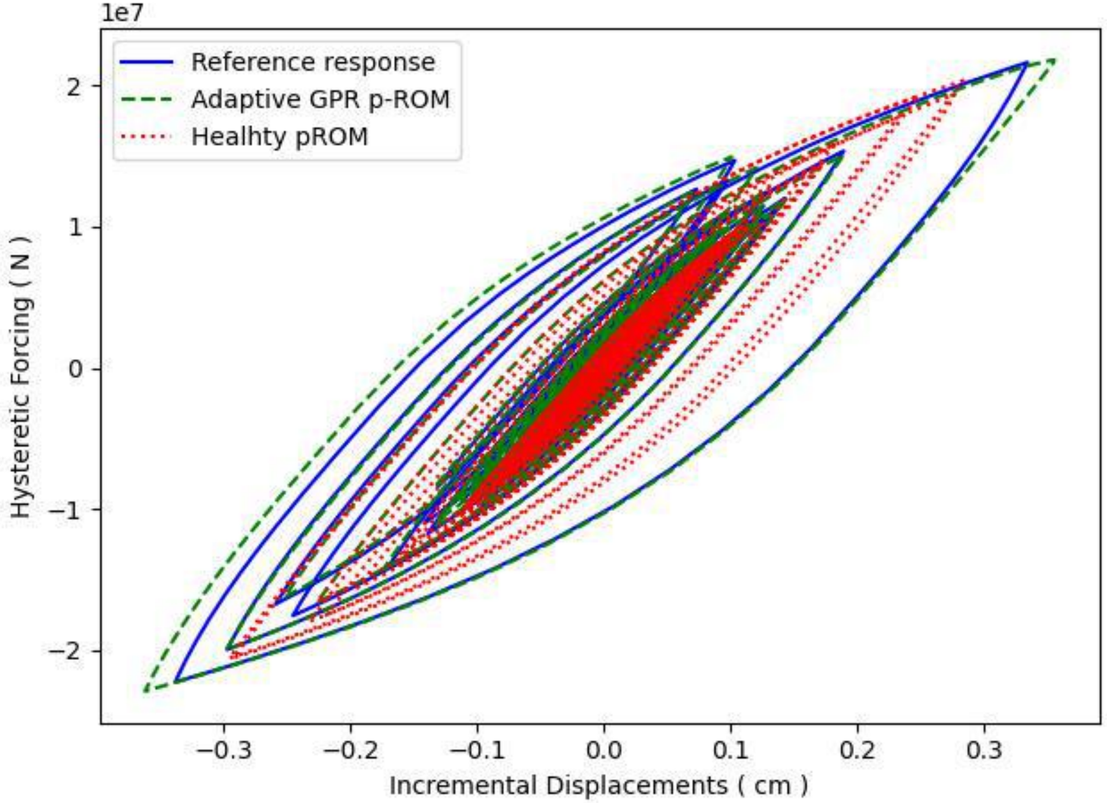


GPR-pROM adapts
projection Basis (***Scenario A***)

Case studies

Accuracy performance of the framework





GPR-pROM adapts
projection Basis (***Scenario C***)

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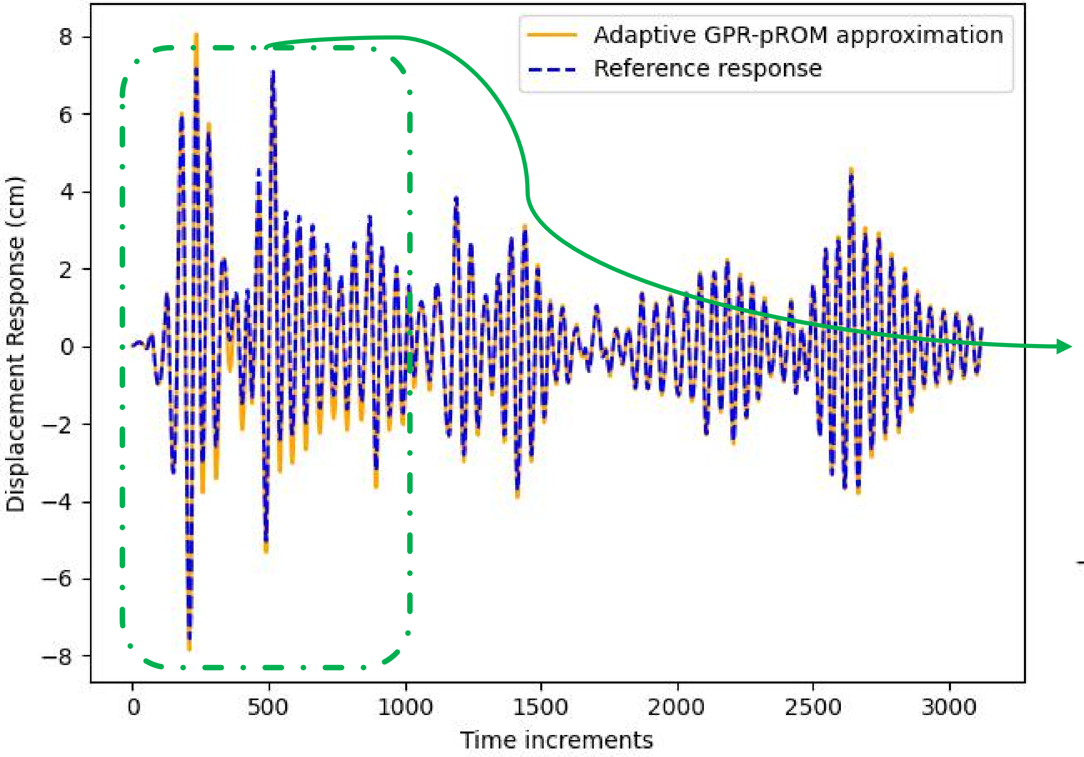
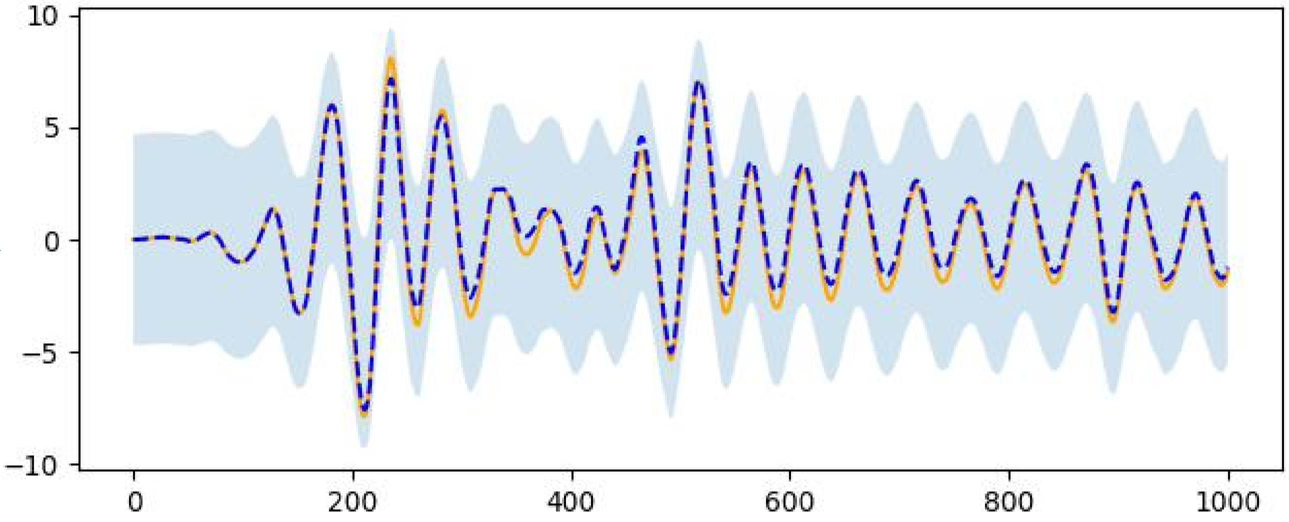
Case studies

Accuracy performance of the framework



GPR-pROM adapts
projection Basis (***Scenario C***)



Confidence Bounds of
GPR-pROM prediction (***Scenario C***)

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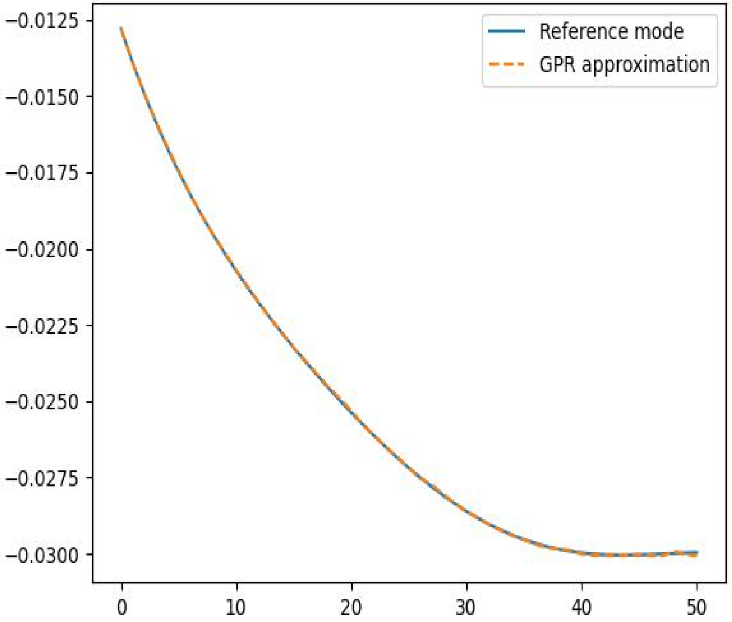
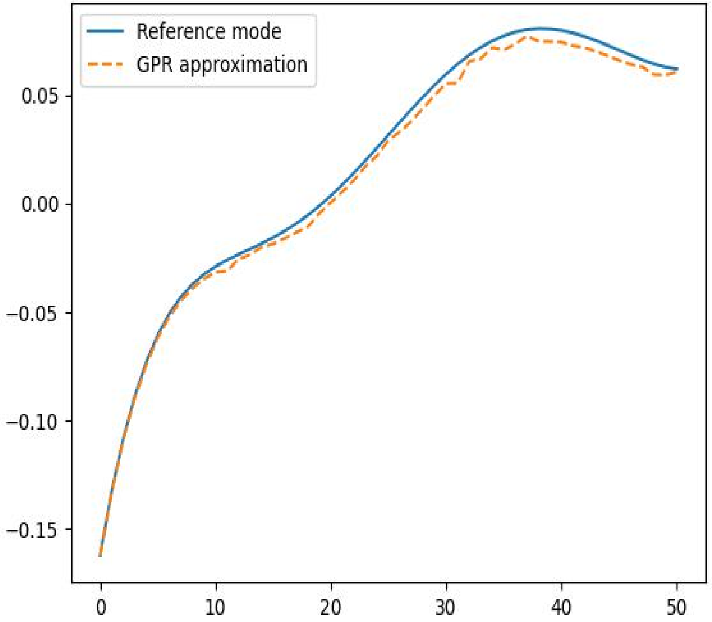
Case studies

Accuracy performance of the framework

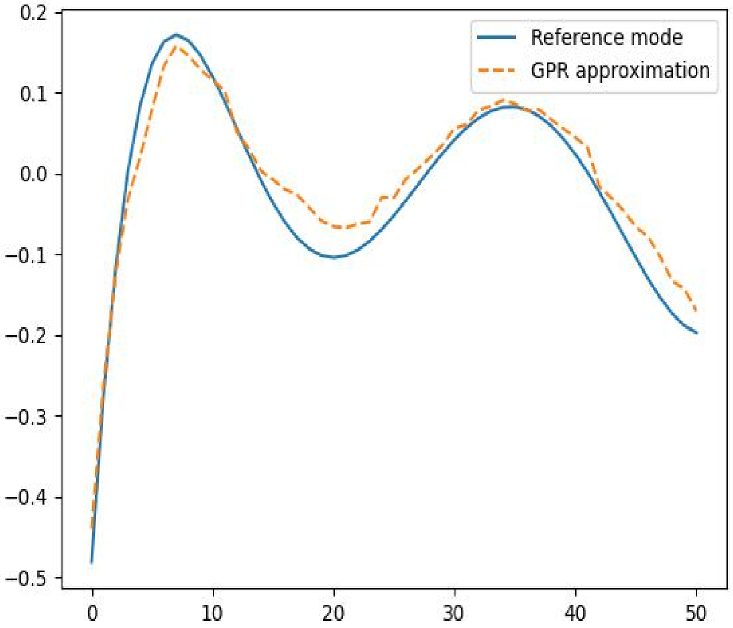
Reduced-order of pROM : 4 modes



GPR approximation
on ***first mode*** (***Scenario C***)



GPR approximation
on ***fourth mode*** (***Scenario C***)



GPR approximation
on ***sixth mode*** (***Scenario C***)

Concluding remarks
Limitations and outlook

The proposed adaptive GPR-pROM framework

- ✓ *Extends performance range* of traditional projection-based pROMs
- ✓ *Captures underlying dynamics* and dependencies *during damage or condition deterioration scenarios*
- ✓ Achieves ***on the fly correction*** of the pROM ***based on sparse measurements***
- ✓ Provides confidence bounds for response estimation
- ✓ May be adapted as an ***approximative, online low-cost surrogate*** for *Structural Health Monitoring* applications

- Hyper-Reduction implications for additional efficiency need further investigation
- GPR approximation scheme fails to capture higher order modes
- GPR approximation performance is strongly dependent on noise level
- GPR input-output channels discretization needs to be automated and optimized

Next short-term steps:

- ❖ Generalize implementation – adjust overall scope:
  Train pROM on earthquake database => Estimate damage in real-case scenarios
- ❖ Couple with filtering scheme to demonstrate potential on parameter/state/input estimation

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Question session