



Coupling of Deep Learning on Graphs and Model Order Reduction for Efficient Preliminary Sizing of Mechanical Structures in Aircraft Crash Simulations

Victor Matray, Faisal Amlani, Frédéric Feyel, David Néron

► To cite this version:

Victor Matray, Faisal Amlani, Frédéric Feyel, David Néron. Coupling of Deep Learning on Graphs and Model Order Reduction for Efficient Preliminary Sizing of Mechanical Structures in Aircraft Crash Simulations. MORTech 2023 – 6th International Workshop on Model Reduction Techniques, Nov 2023, Gif sur Yvette, France. hal-04585040

HAL Id: hal-04585040

<https://hal.science/hal-04585040>

Submitted on 23 May 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Coupling of Deep Learning on Graphs and Model Order Reduction for Efficient Preliminary Sizing of Mechanical Structures in Aircraft Crash Simulations

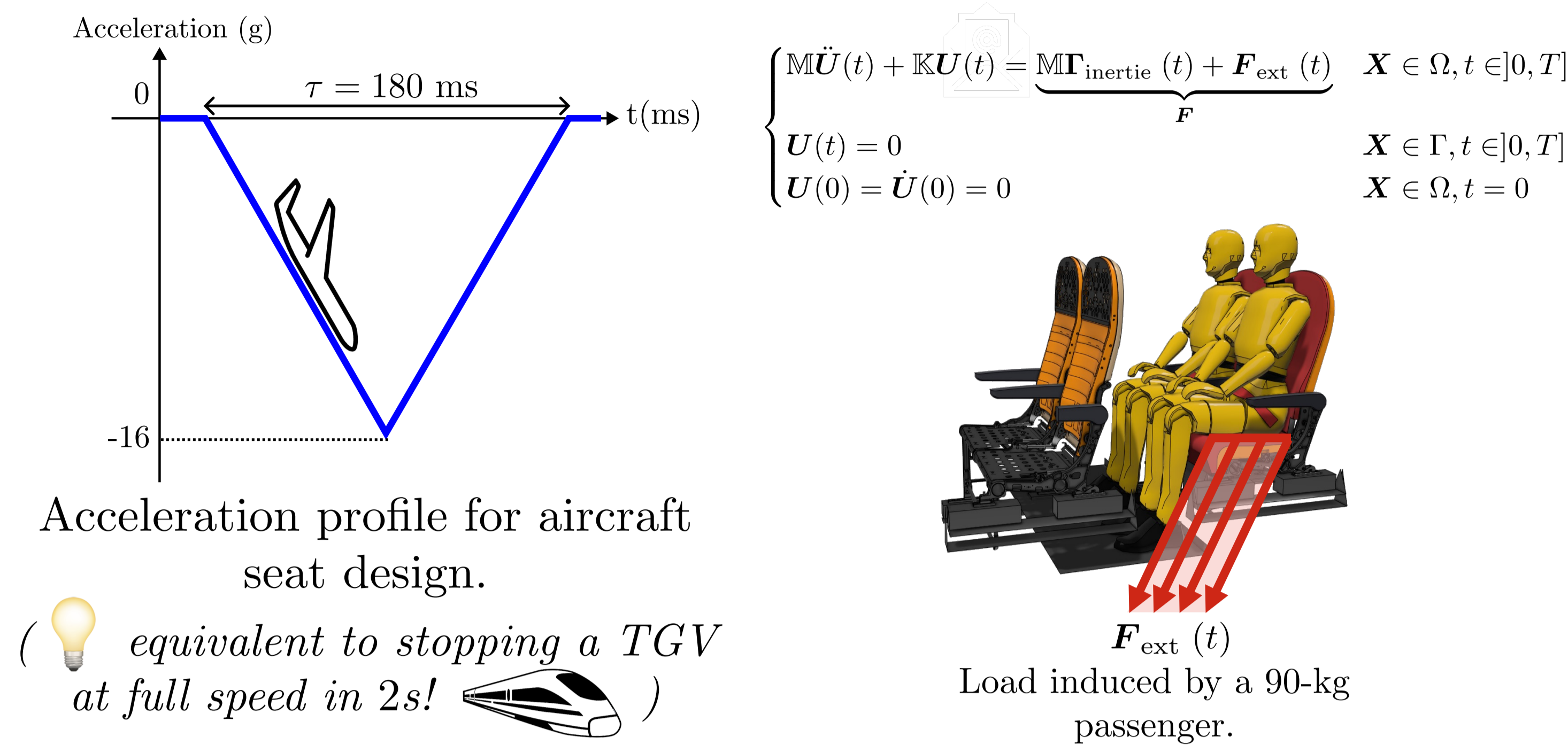
Victor Matray ^a, Faisal Amlani ^a, Frédéric Feyel ^{b,a}, David Néron ^a

^a LMPS - Laboratoire de Mécanique Paris-Saclay, Université Paris-Saclay, CentraleSupélec, ENS Paris-Saclay, CNRS, 4 Av. des Sciences, 91190, Gif-sur-Yvette, France.

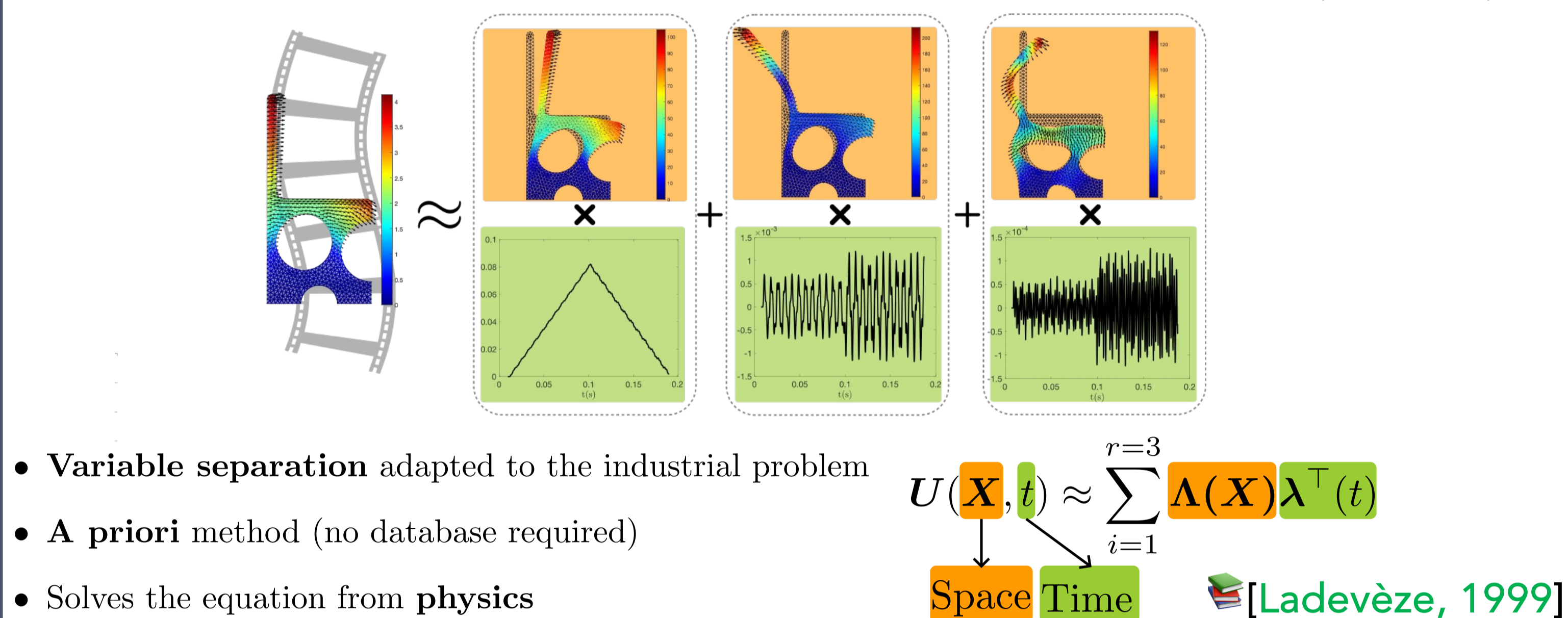
^b Safran Tech, Digital Sciences & Technologies Department, Rue des jeunes bois, Châteaufort, 78114, Magny-les-Hameaux, France.

Keywords: Reduced Model (POD-PGD), Non-Parametric Problem, Deep Learning, Graph Neural Networks

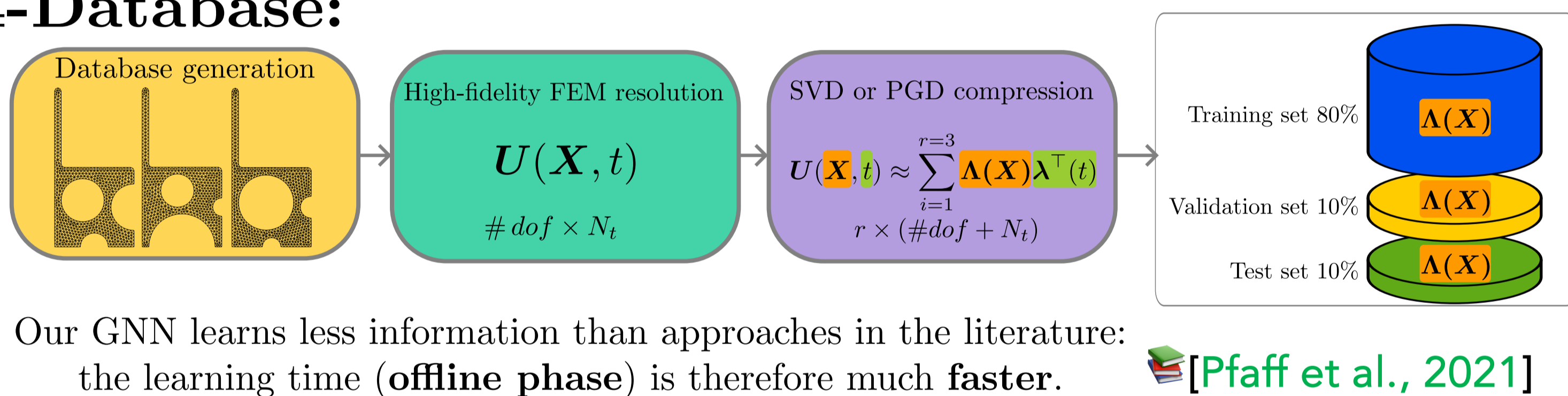
1-Loading case:



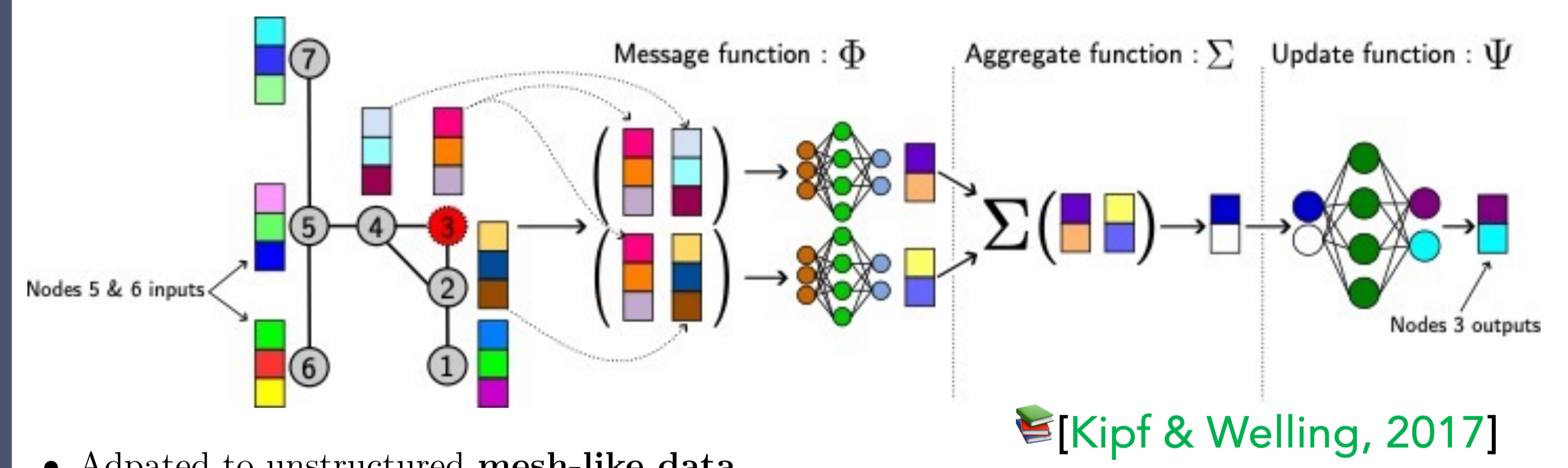
2-The Proper Generalized Decomposition (PGD):



4-Database:



3-Graph Neural Networks (GNN):



- Adapted to unstructured mesh-like data
- Does not depend on the number of nodes and edges in the input graph, only in the number of input features (through permutation-invariant aggregate function)
- High flexibility and generalisability

Developed spatial convolution layer:

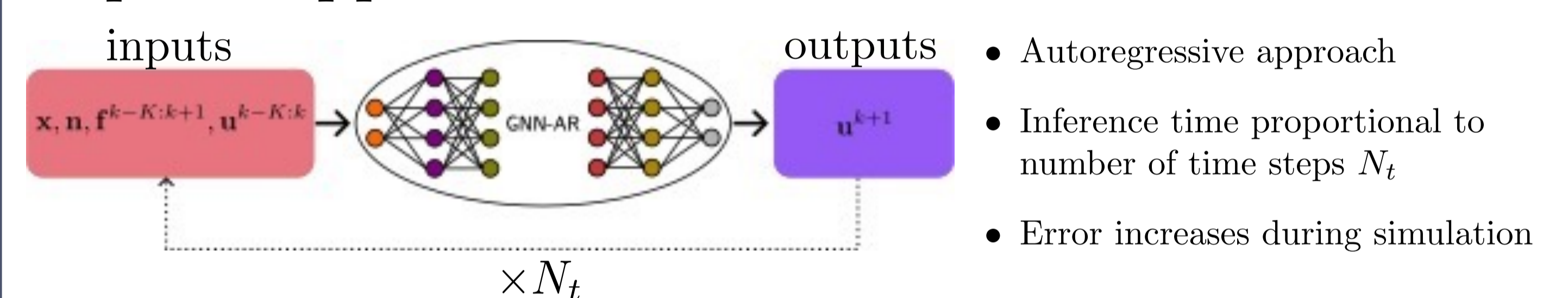
node i embedding: $\mathbf{v}_i^0 = \text{MLP}_{\text{encoder}}(\mathbf{F}_i, \mathbf{n}_i)$,

edge $j \rightarrow i$ message: $\mathbf{m}_{ij}^l = \phi(\mathbf{v}_i^l, \mathbf{v}_j^l, \mathbf{F}_i, \mathbf{F}_j, \mathbf{n}_i, \mathbf{n}_j)$, [Huang et al., 2018]

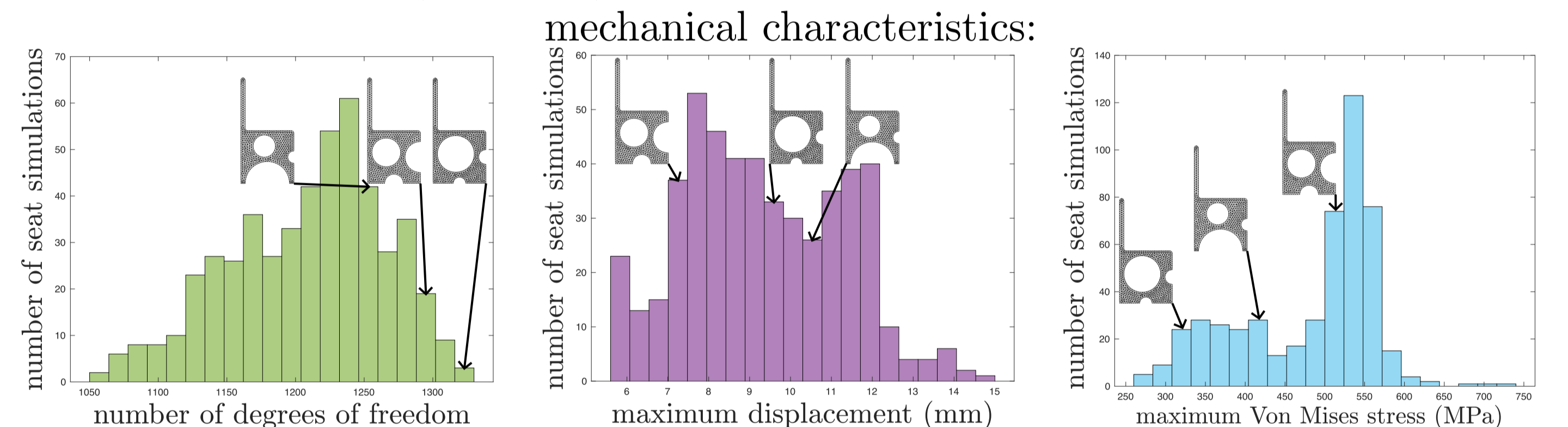
node i update: $\mathbf{v}_i^{l+1} = \psi(\mathbf{v}_i^l, \sum_{j \in \mathcal{N}(i)} \mathbf{m}_{ij}^l, \mathbf{F}_i, \mathbf{n}_i)$,

node i final state: $\mathbf{\Lambda}_i^{\text{GNN}} = \text{MLP}_{\text{decoder}}(\mathbf{v}_i^L)$ [Brandstetter, 2022]

Popular approach in the literature: [Pfaff et al., 2021]



The small database (500 seats) contains a wide variety of seats with very different mechanical characteristics:



5-Proposed algorithm and results:

We only consider seats **never seen by the network** during training (test base).

We want to calculate the time modes: λ

Finite element operator calculation: \mathbf{M} et \mathbf{K}

Galerkin projection on \mathbf{P} :

$$\mathbf{P}^T \cdot \mathbf{M} \cdot \mathbf{P} \ddot{\mathbf{\lambda}}^T + \mathbf{P}^T \cdot \mathbf{K} \cdot \mathbf{P} \lambda^T = \mathbf{P}^T \cdot \mathbf{F}$$

-POD trick-
use a suitable scalar product to precondition the problem,
 $\langle \circ, \square \rangle_{\mathbb{K}-1} = \circ^T \mathbb{K}^{-1} \square$

Finally, we only solve the small ODE system ($r \times r$):

$$\mathbf{P}^T \mathbb{K}^{-1} \mathbf{M} \cdot \mathbf{P} \ddot{\mathbf{\lambda}}^T + \mathbf{P}^T \mathbb{I} \cdot \mathbf{P} \lambda^T = \mathbf{P}^T \mathbb{K}^{-1} \mathbf{F}$$

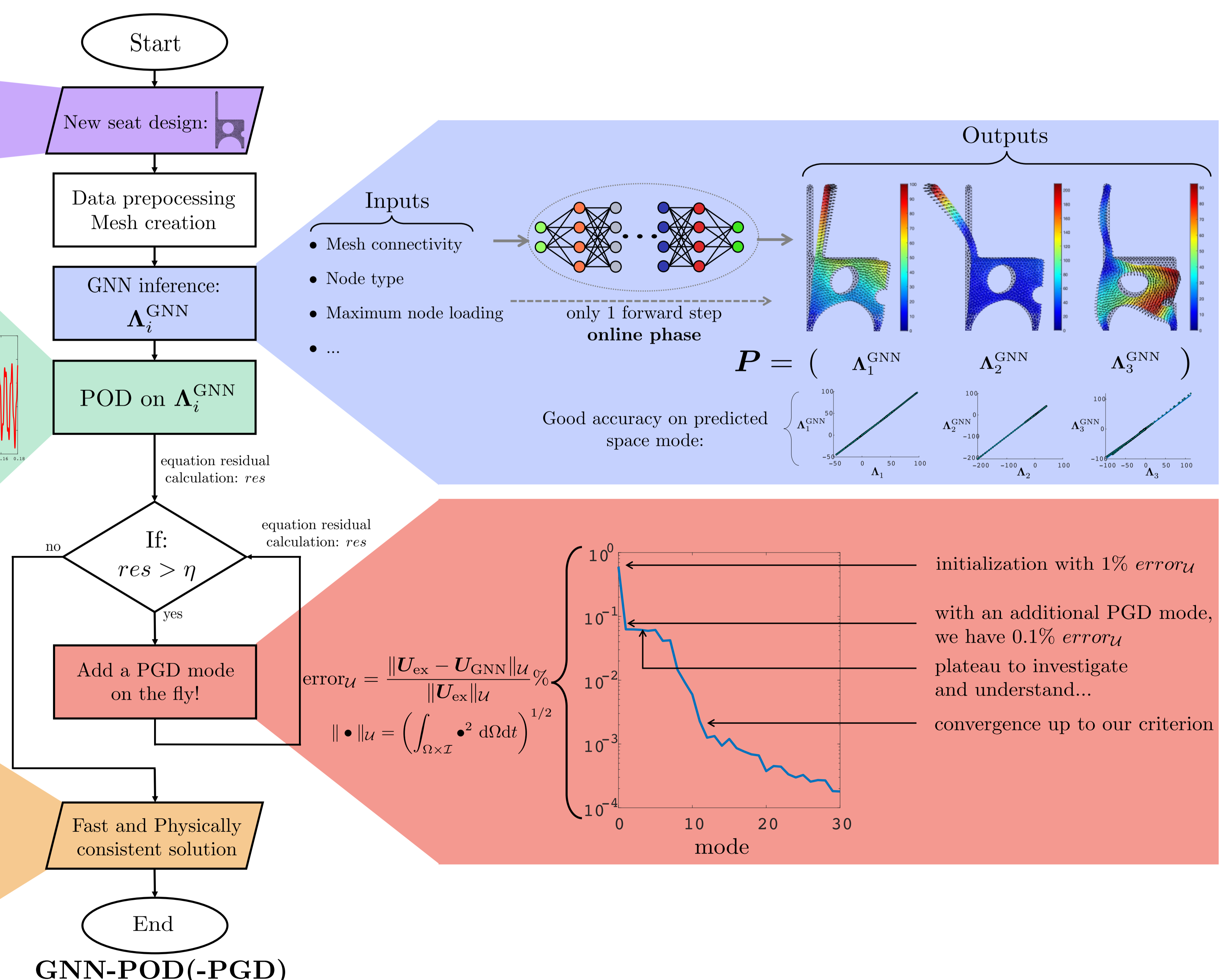
For the 50 seats tested, we obtained an $error_u$ of less than 1% immediately after the GNN-POD phase.

Furthermore, as soon as an on-the-fly PGD mode is added, we obtain an $error_u$ of at least less than 0.1% for all the seats tested.

In all cases, we solve the physical equation:

physics has the final say!

For all the seats tested, we speed up the calculation thanks to the prediction of GNN spatial modes, but if this were not the case, we wouldn't take longer than a reduced-order PGD model.



This work was granted access to the HPC resources of IDRIS under the allocation 2023-[AD011014260] made by GENCI.