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

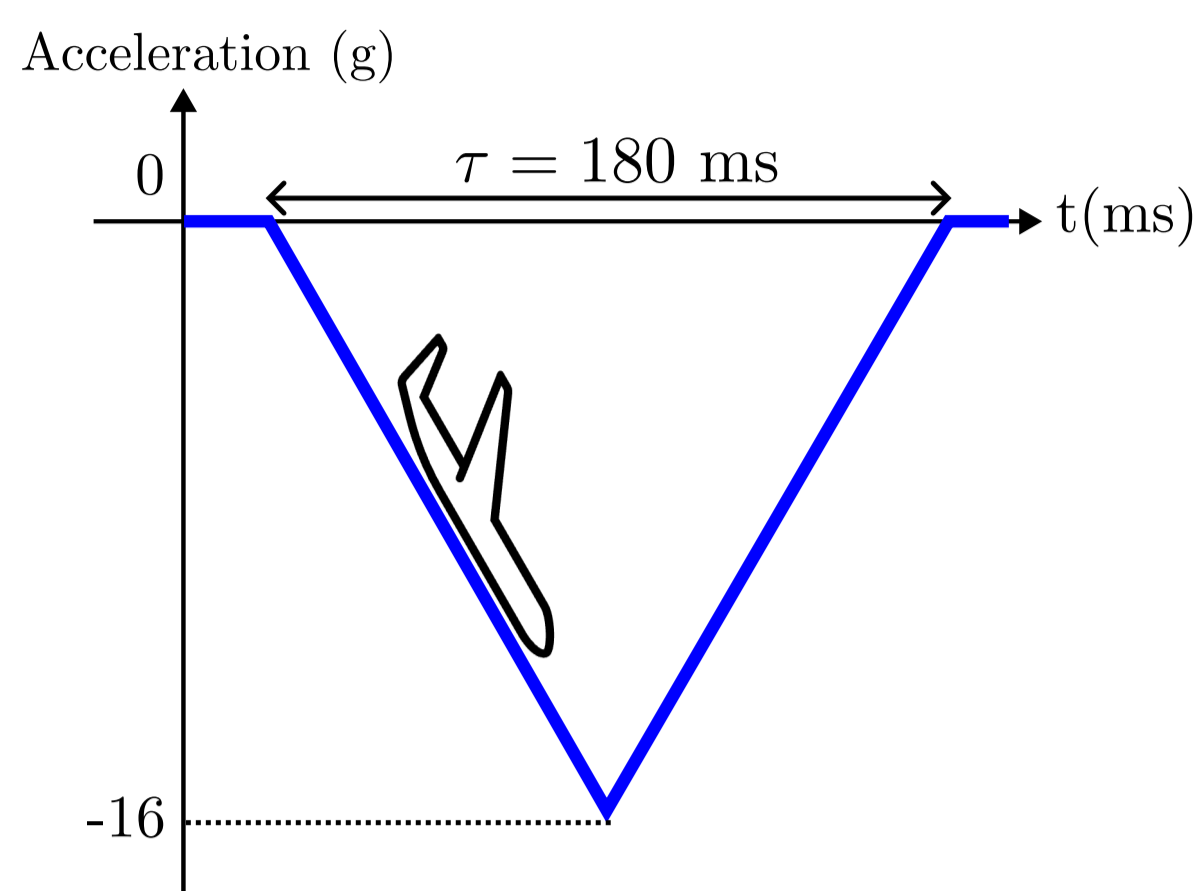
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Keywords: Reduced Model (POD-PGD), Non-Parametric Problem, Deep Learning, Graph Neural Networks

1-Loading case:



Acceleration profile for aircraft seat design.

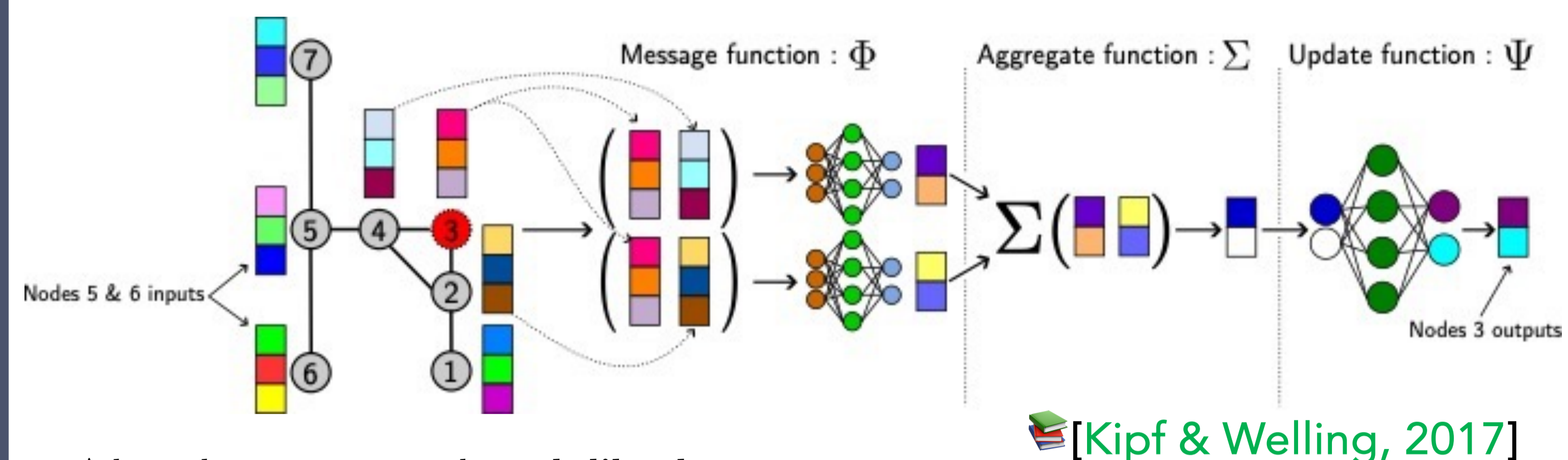
(💡 equivalent to stopping a TGV at full speed in 2s! 🚅)

$$\begin{cases} M\ddot{U}(t) + KU(t) = MF_{\text{inertie}}(t) + F_{\text{ext}}(t) & X \in \Omega, t \in]0, T[\\ U(t) = 0 & X \in \Gamma, t \in]0, T[\\ U(0) = \dot{U}(0) = 0 & X \in \Omega, t = 0 \end{cases}$$



Load induced by a 90-kg passenger.

3-Graph Neural Networks (GNN):



[Kipf & Welling, 2017]

- 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:

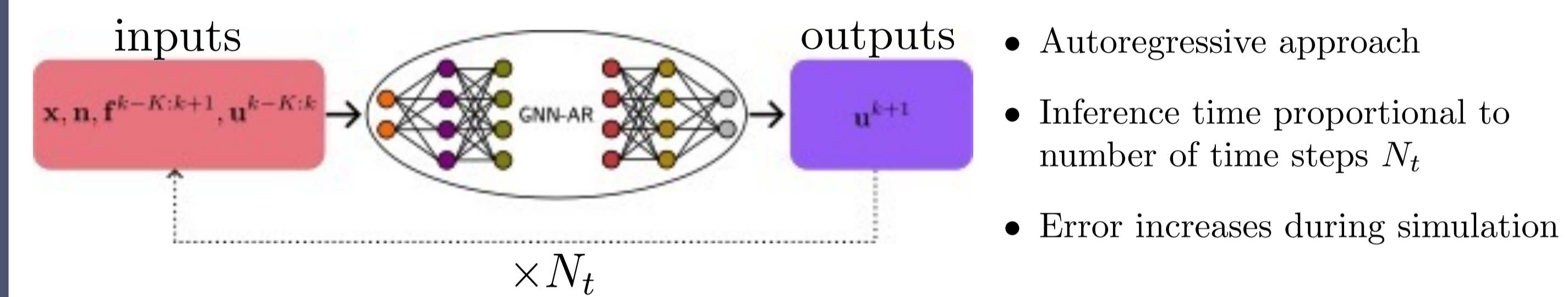
node i embedding: $v_i^0 = \text{MLP}_{\text{encoder}}(F_i, n_i)$,

edge $j \rightarrow i$ message: $m_{ij}^l = \phi(v_i^l, v_j^l, F_i, F_j, n_i, n_j)$, [Huang et al., 2018]

node i update: $v_i^{l+1} = \psi(v_i^l, \sum_{j \in \mathcal{N}(i)} m_{ij}^l, F_i, n_i)$,

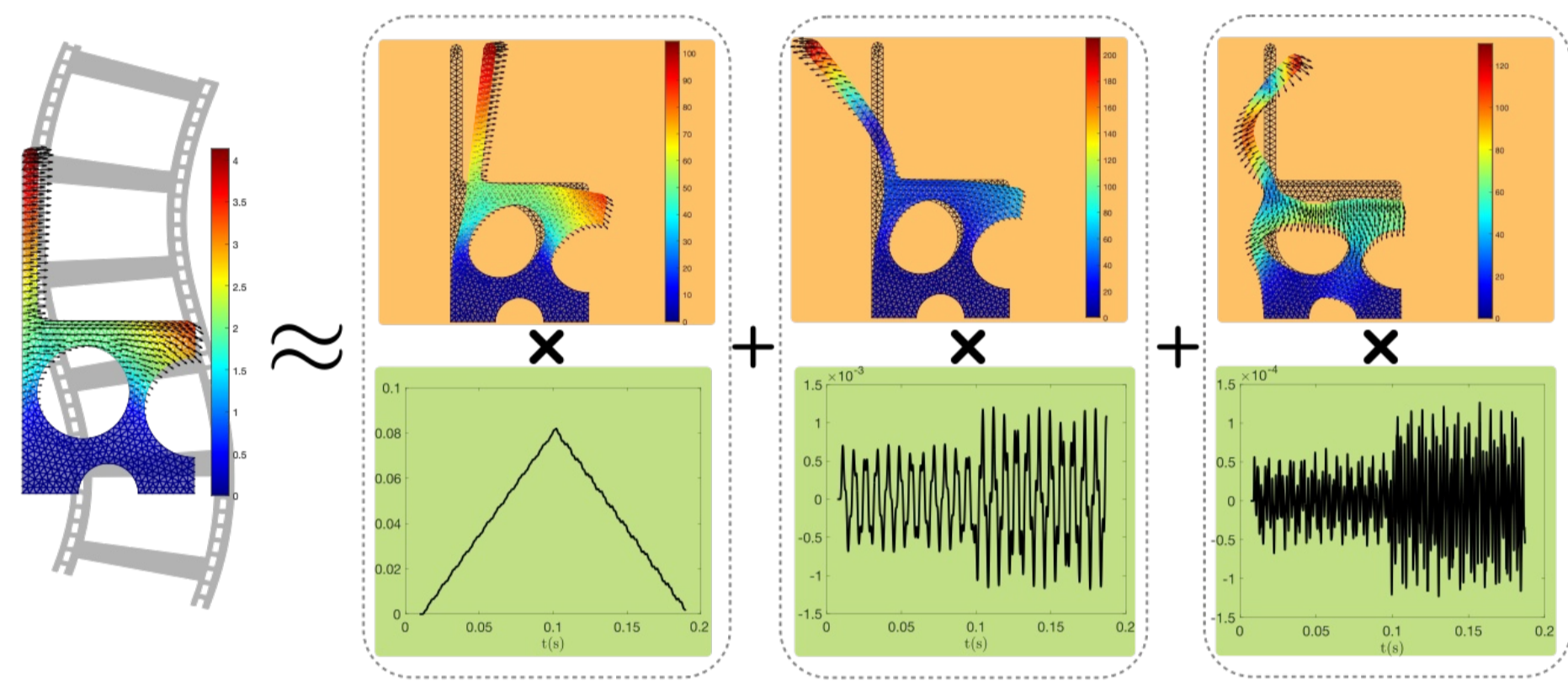
node i final state: $\Lambda_i^{\text{GNN}} = \text{MLP}_{\text{decoder}}(v_i^L)$ [Brandstetter, 2022]

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



- Autoregressive approach
- Inference time proportional to number of time steps N_t
- Error increases during simulation

2-The Proper Generalized Decomposition (PGD):

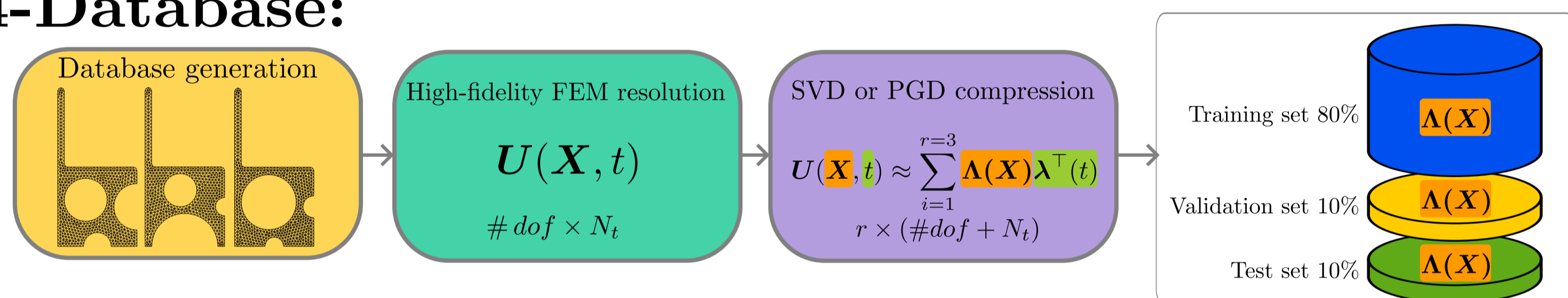


- Variable separation adapted to the industrial problem
- A priori method (no database required)
- Solves the equation from physics

$$U(X, t) \approx \sum_{i=1}^{r=3} \Lambda(X) \lambda^T(t)$$

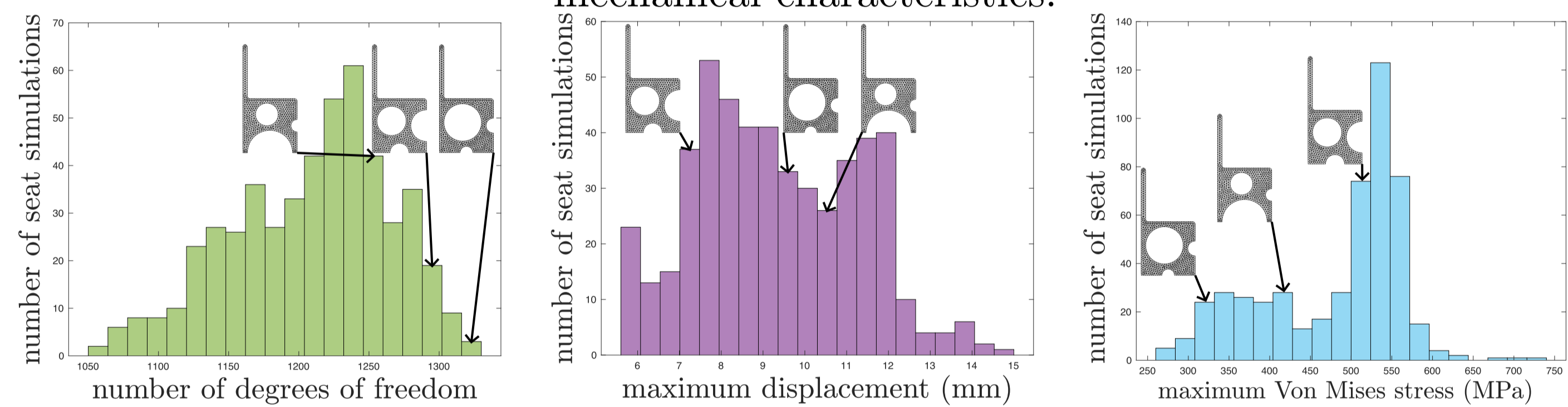
Space Time [Ladevèze, 1999]

4-Database:



Our GNN learns less information than approaches in the literature: the learning time (offline phase) is therefore much faster. [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: M et K

Galerkin projection on P :

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

-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 ($r \times r$):

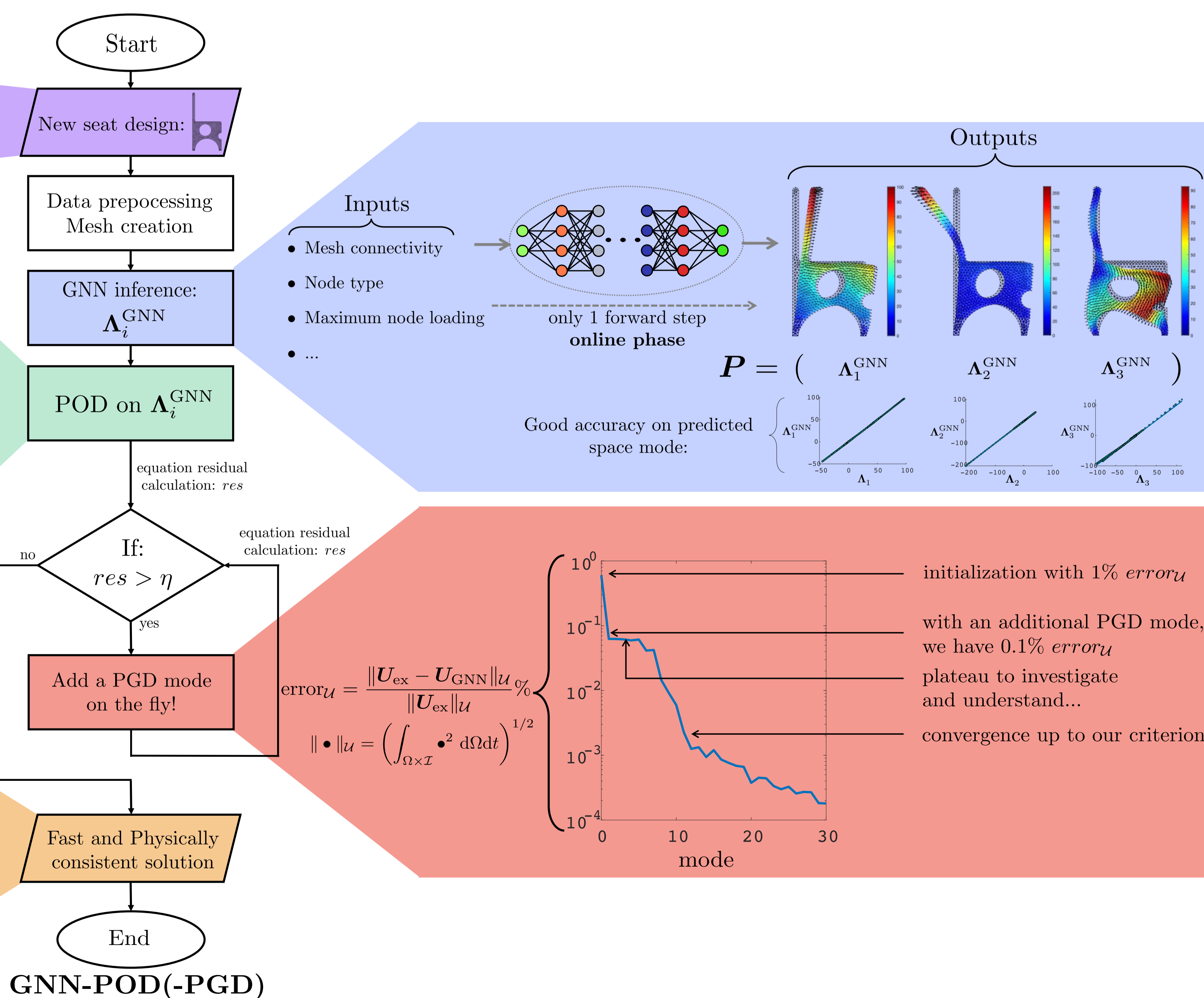
$$P^T \mathbb{K}^{-1} M \cdot P \ddot{\lambda}^T + P^T \mathbb{I} \cdot P \lambda^T = P^T \mathbb{K}^{-1} F$$

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.



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