

# Deep Material Networks

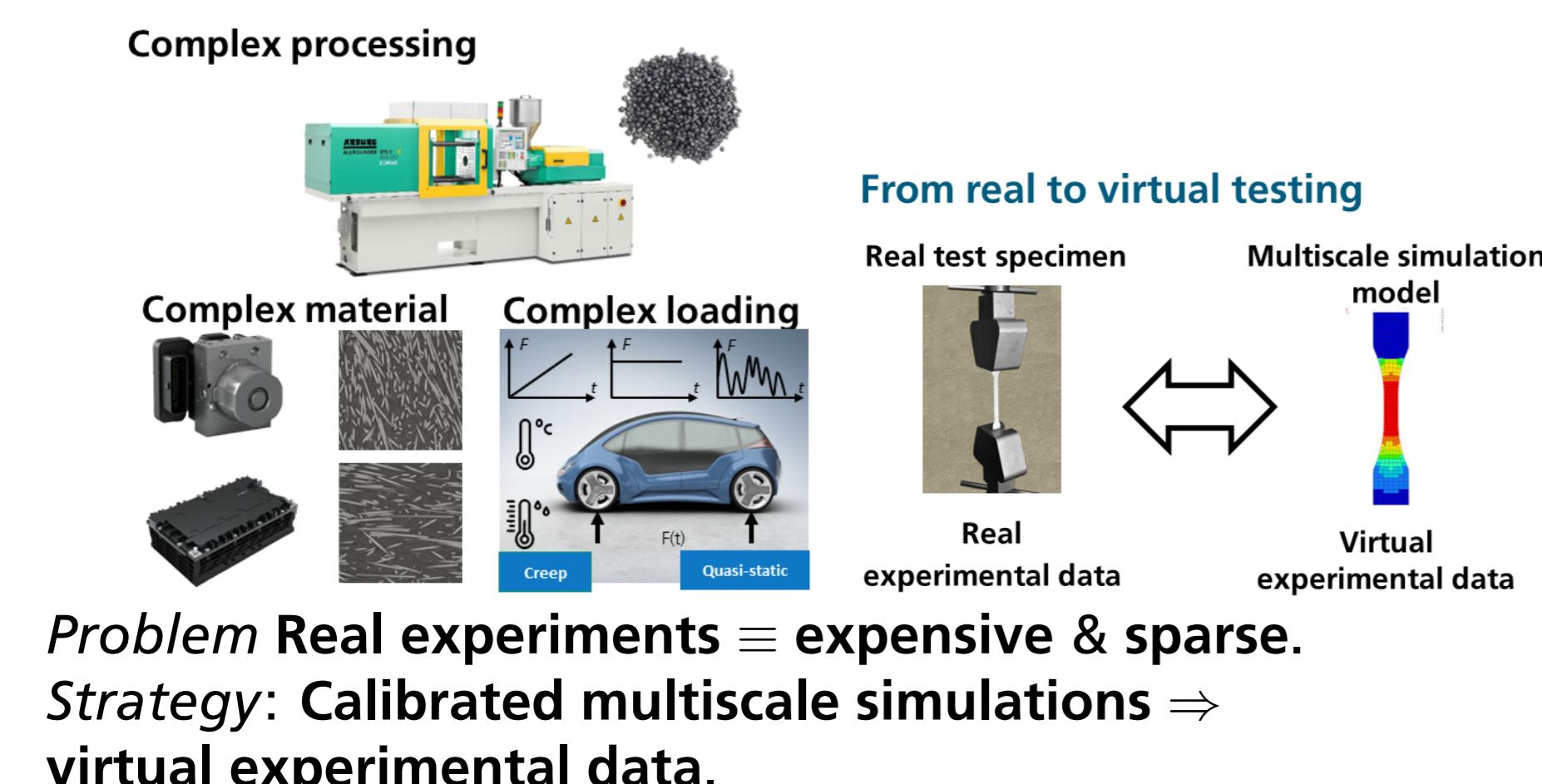
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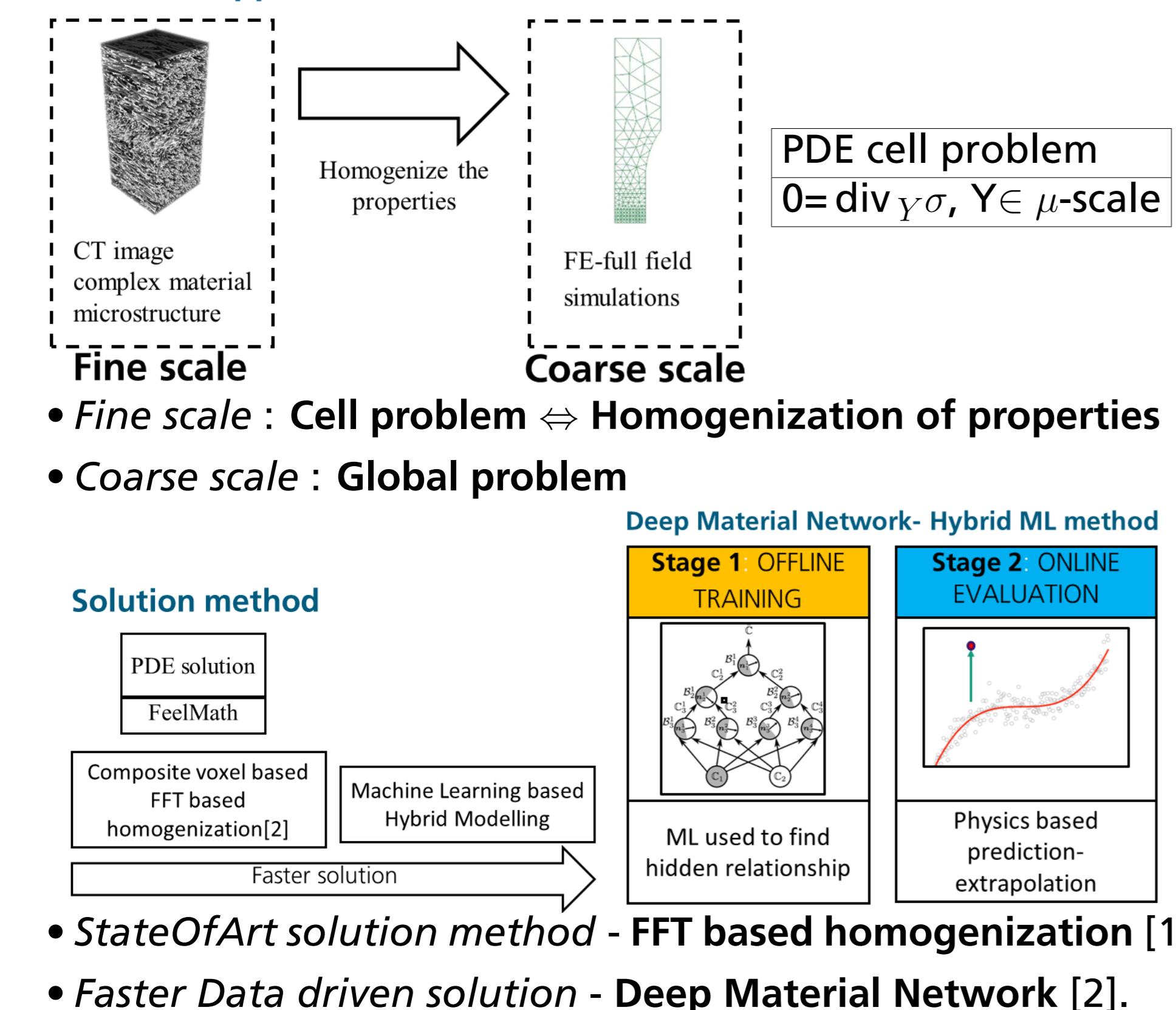
## Motivation

### Reliability despite complexity

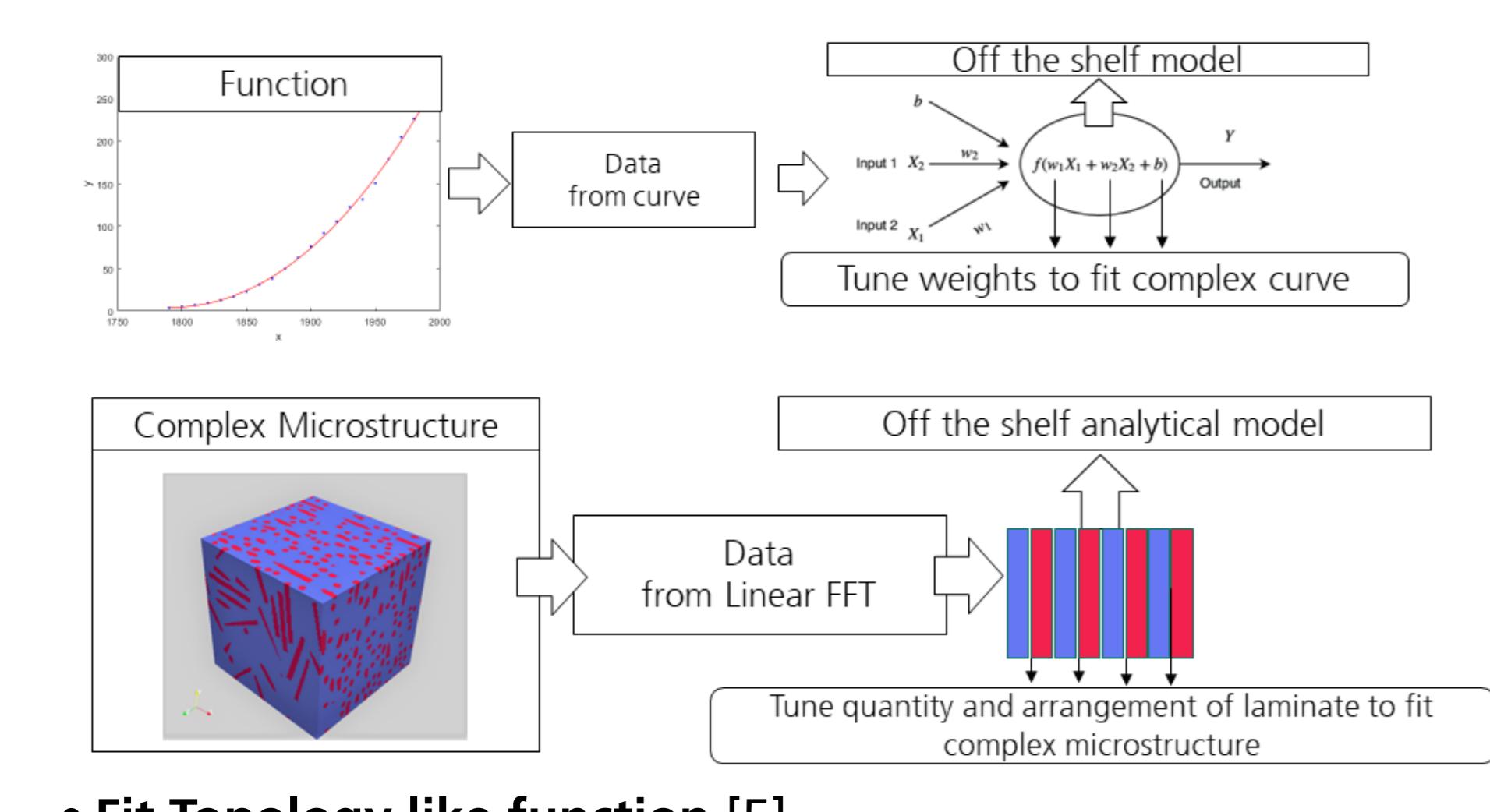


## Deep Material Network (DMN)

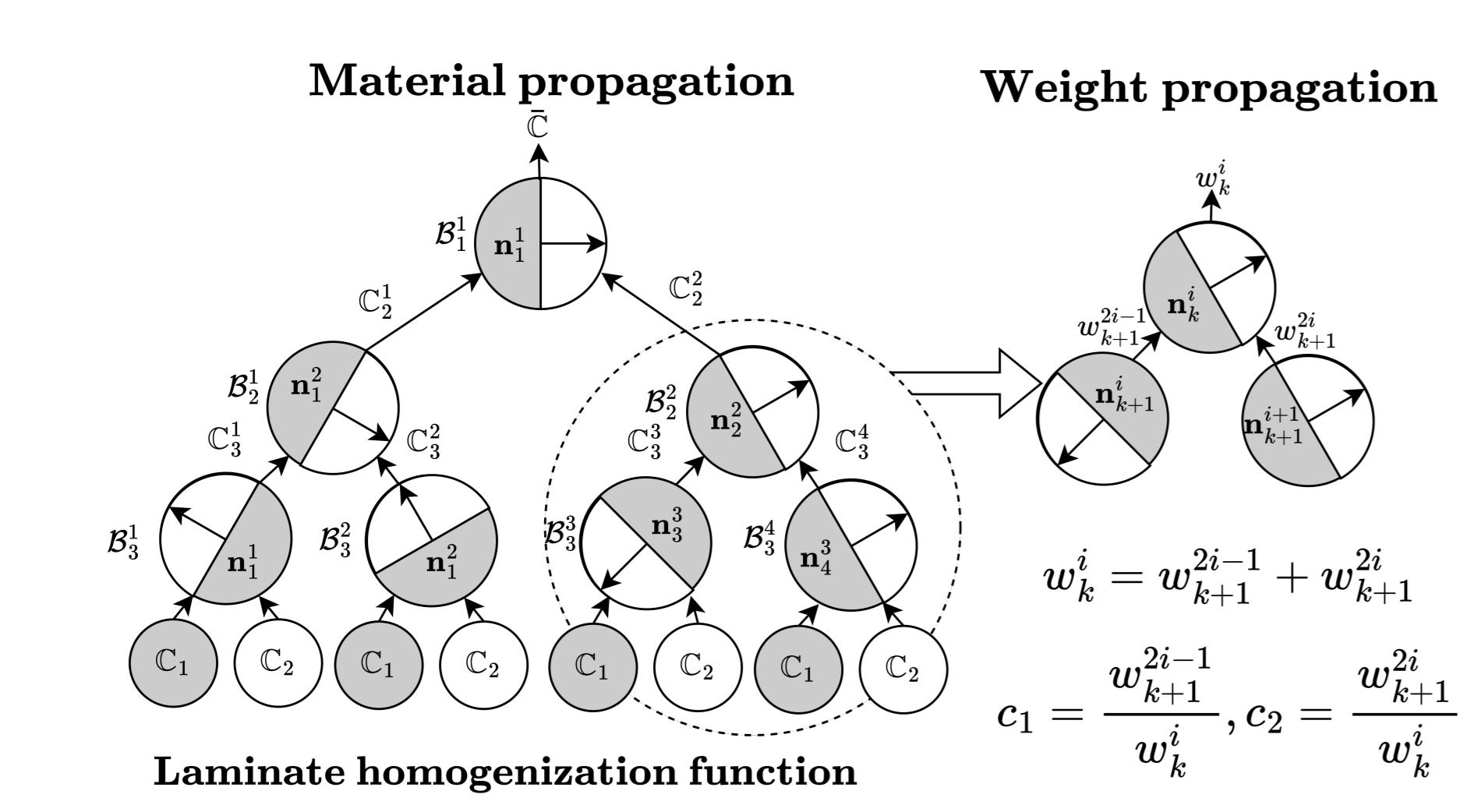
### Two scale approach



### Intuition of Linear elastic fitting



## Hierarchical laminate network



Problem:  $J \rightarrow \min$

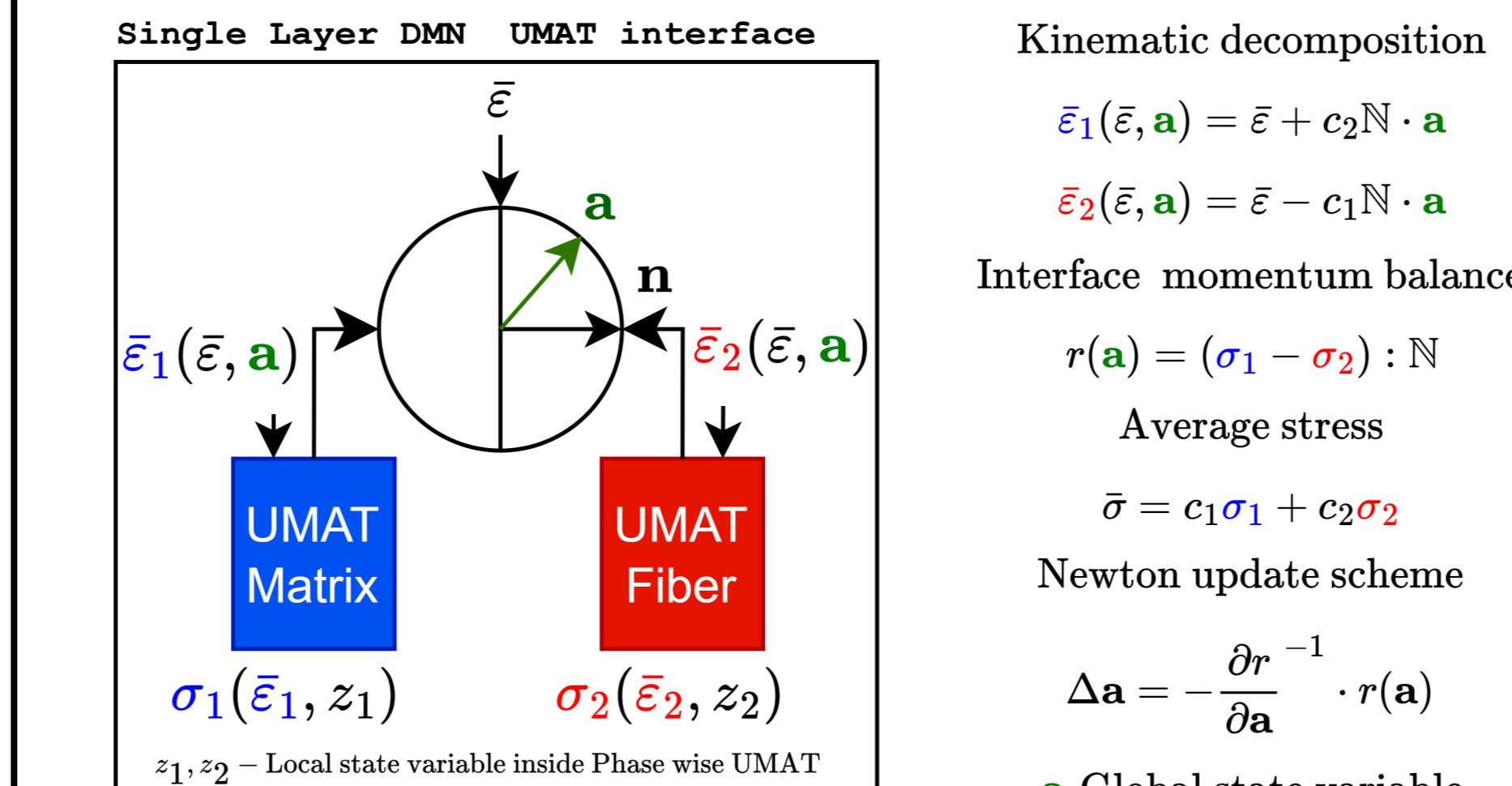
$J_M = 0 \forall M - \text{phase}$

$$J(\mathbf{n}, \mathbf{w}) = J_{Data} + \sum_{j=1}^M \lambda_j J_j$$

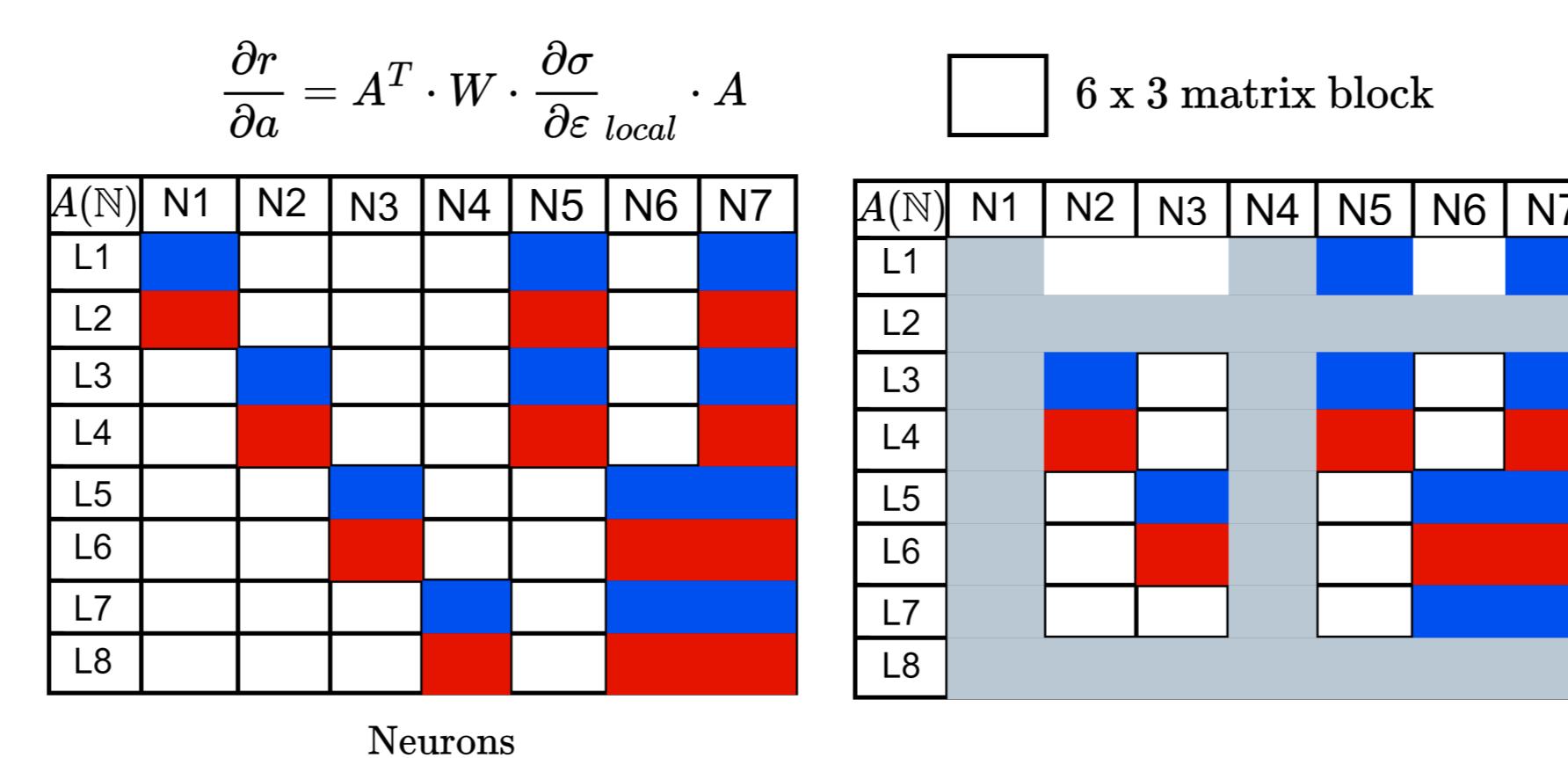
$$J_{Data} = \frac{1}{N_b} \sum_{i=1}^{N_b} \left( \frac{\|\bar{C}_i^{FFT} - \bar{C}_i^{DMN}\|_1}{\|\bar{C}_i^{FFT}\|_1} \right)^2 \quad J_M = \left( \sum_{i=1}^{2^{k-1}} \frac{w_K^{i,M}}{2^{k-1}} - c^M \right)^2$$

• Parameters:  $w$  - Weights,  $n$  - Direction of laminate

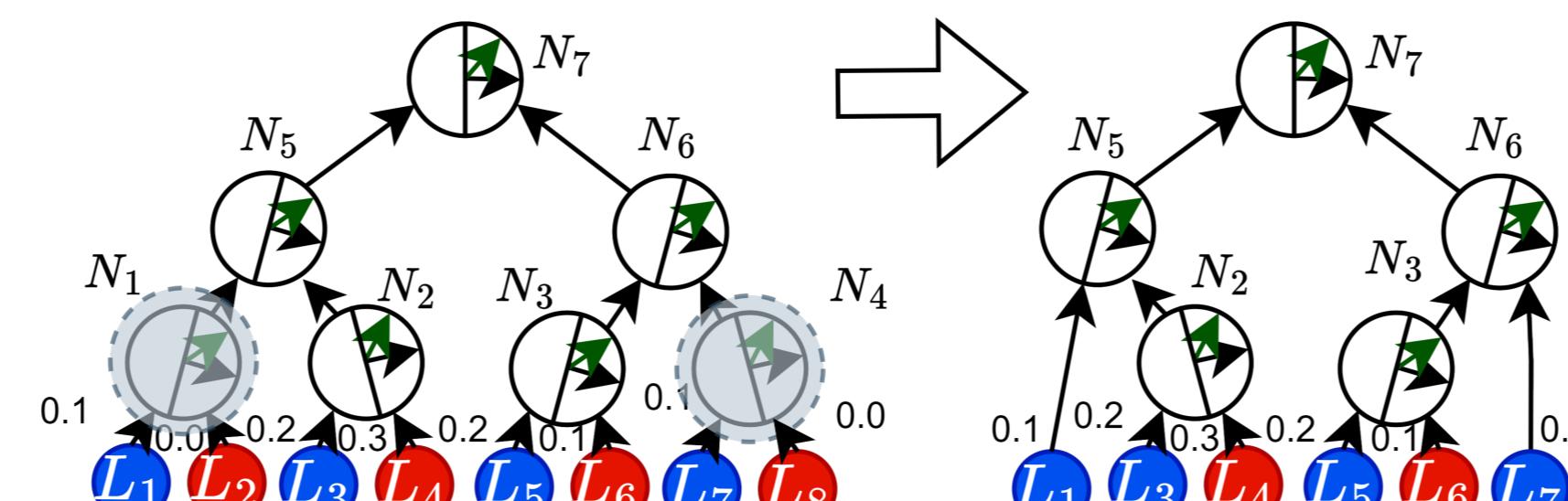
## Nonlinear extrapolation- DMN Online



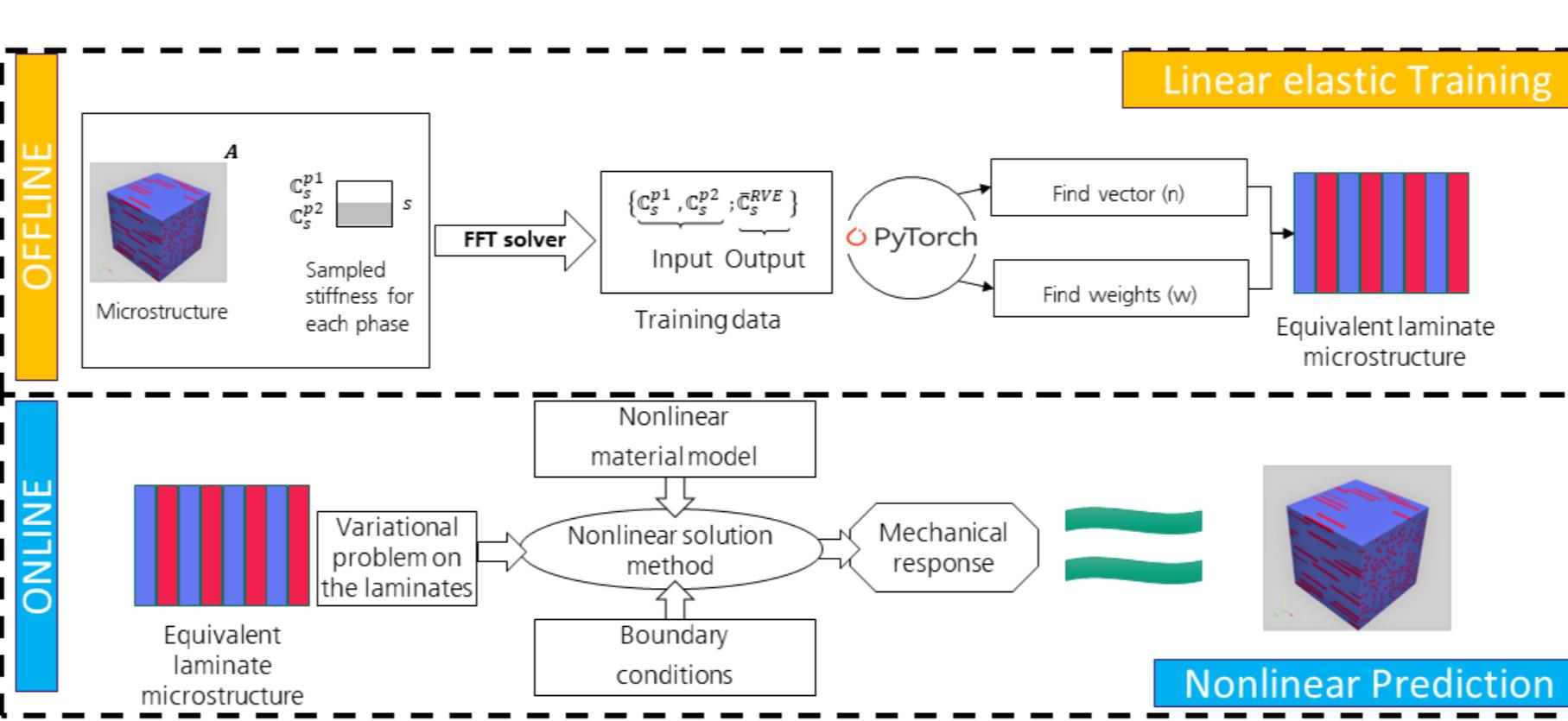
Vectorization and sparsification of Newton scheme



Neuron elimination and pruning



## Basic workflow and steps



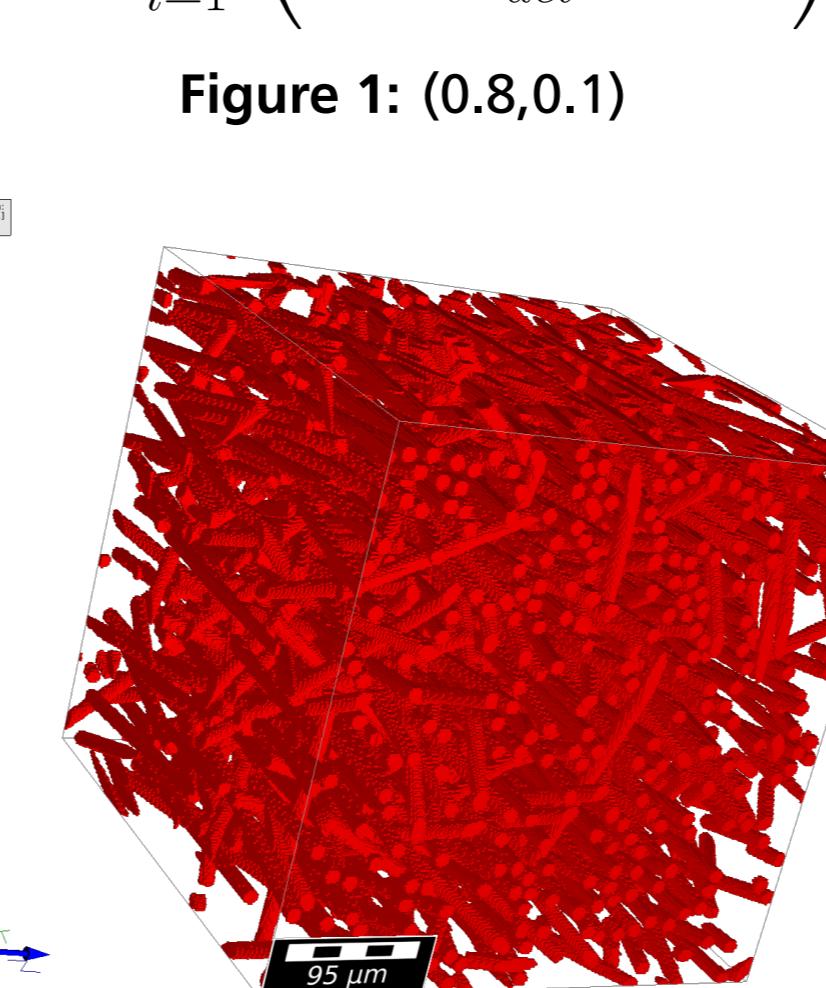
## Viscoelastic sampling and parameter choice

$$\mathbb{C}_f = 3 \cdot K_f \cdot \mathbb{P}_1 + 2 \cdot G_f \cdot \mathbb{P}_2$$

$$\mathbb{C}_M = 3 \cdot K_0 \cdot \mathbb{P}_1 + 2 \cdot \left( G_0 + \sum_{i=1}^{N_M} G_{M,i} \cdot (1 - y_{s,i})^{\lambda_i} \right) \cdot \mathbb{P}_2$$

$$\mathbb{P}_1 = \mathbb{I}^{vol}, \mathbb{P}_2 = \mathbb{I}^{dev}, y_s \in U(0, 1), N_M = 9$$

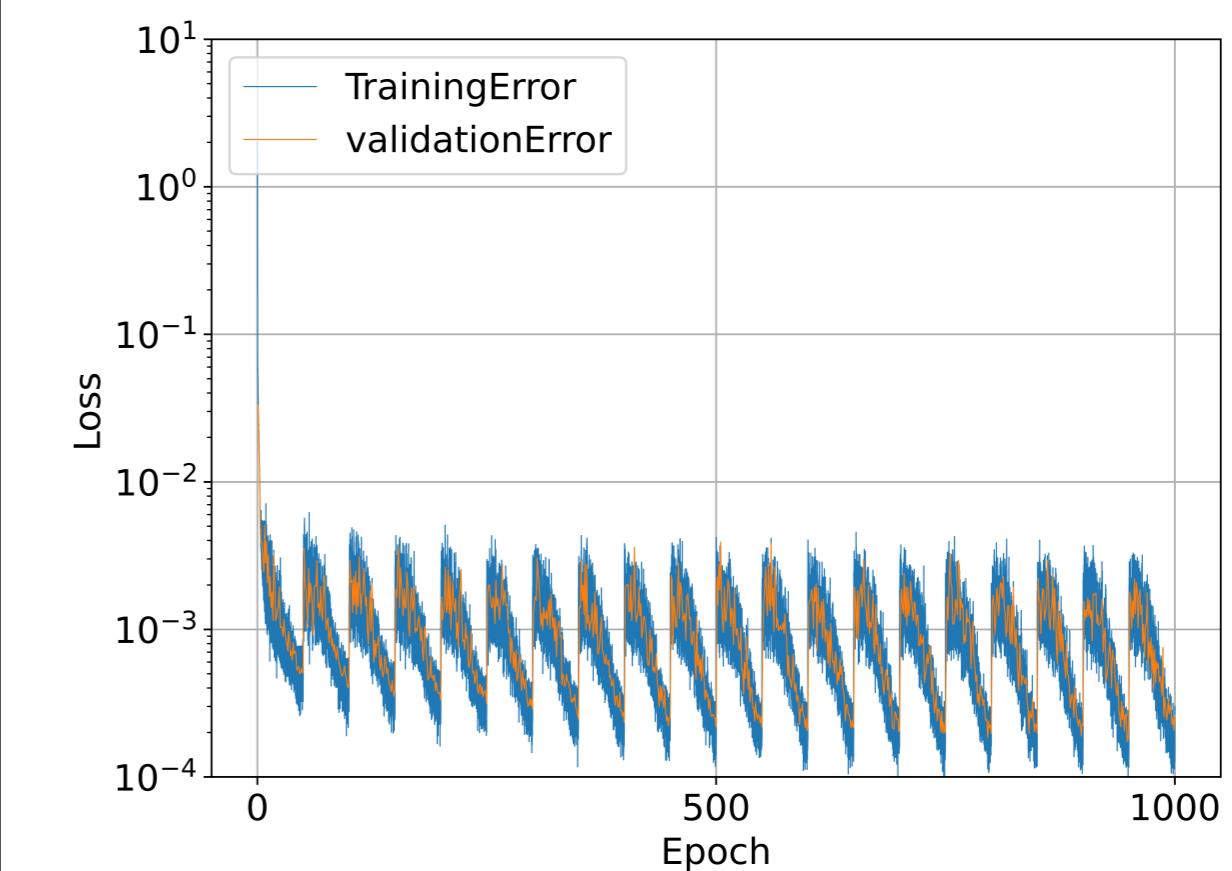
Parameters	Values
Microstructure	
Fiber length $\mu m$	200
Fiber diameter $\mu m$	10
Fiber volume fraction	16%
Number of voxels	256
Voxel length $\mu m$	1.5
Data	
Samples	1280
Train validation split	0.8
Test samples	51
Hyper-parameters	
$N_b$ , batch size	8
$\lambda_M$	100
Optimizer	Adam
Lr modulation	SGDR
$Epochs_{max}$	1000
Layer Depth	8
$Lr \alpha_{min}$	0.0015
$Lr \alpha_{max}$	0.015
Restart Epoch M	50



### Nonlinear Tests chosen

Uniaxial testing	$\varepsilon_{max} = 4\%$
$\dot{\varepsilon} = 0.0005$	6 directions
$\dot{\varepsilon} = 0.005$	6 directions
$\dot{\varepsilon} = 0.05$	6 directions
$\dot{\varepsilon} = 0.5$	6 directions
Creep testing	20 seconds
$\varepsilon = 4\%$	6 directions
Total tests	30

## Offline hyper-parameter-tuning

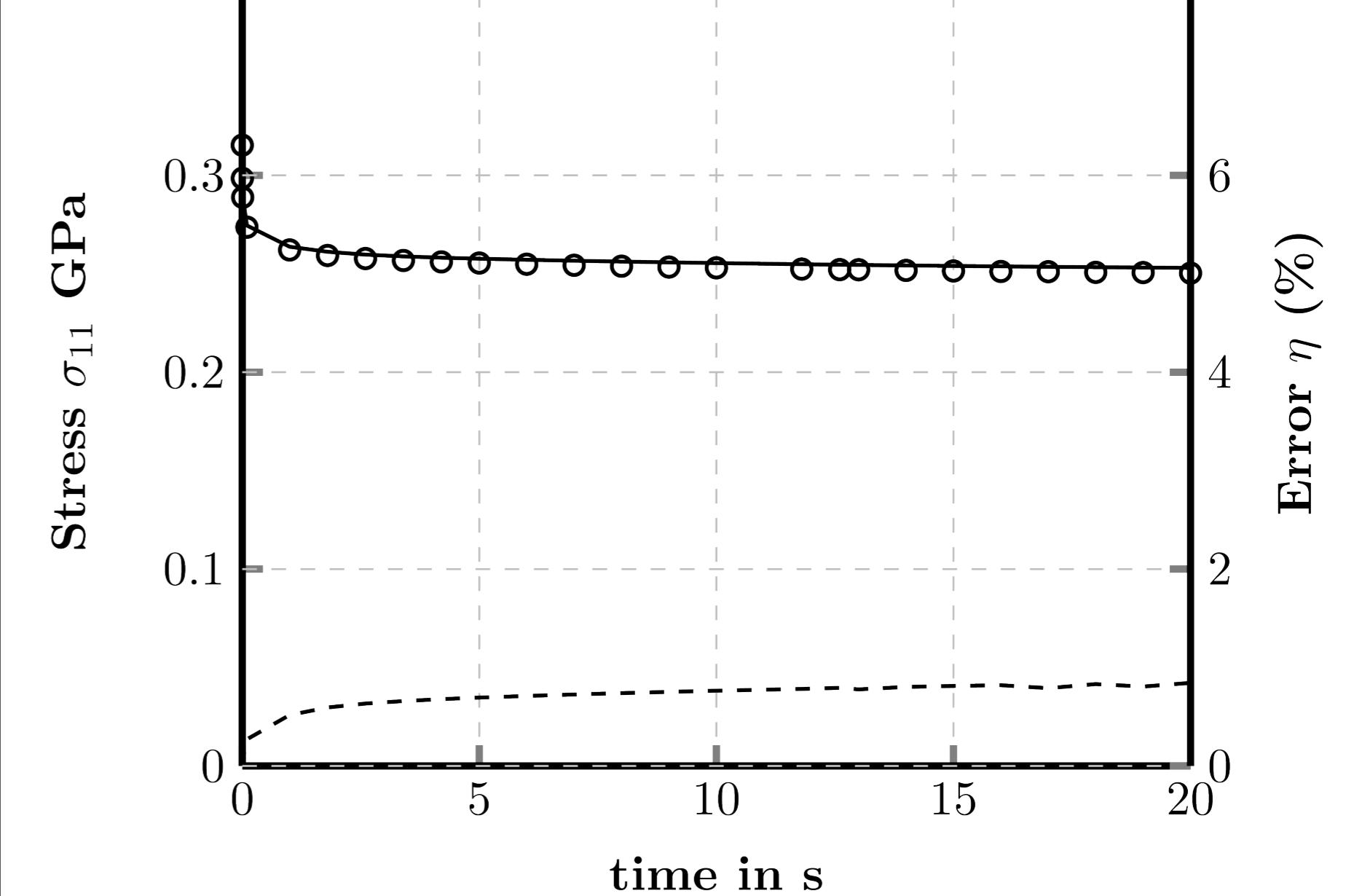
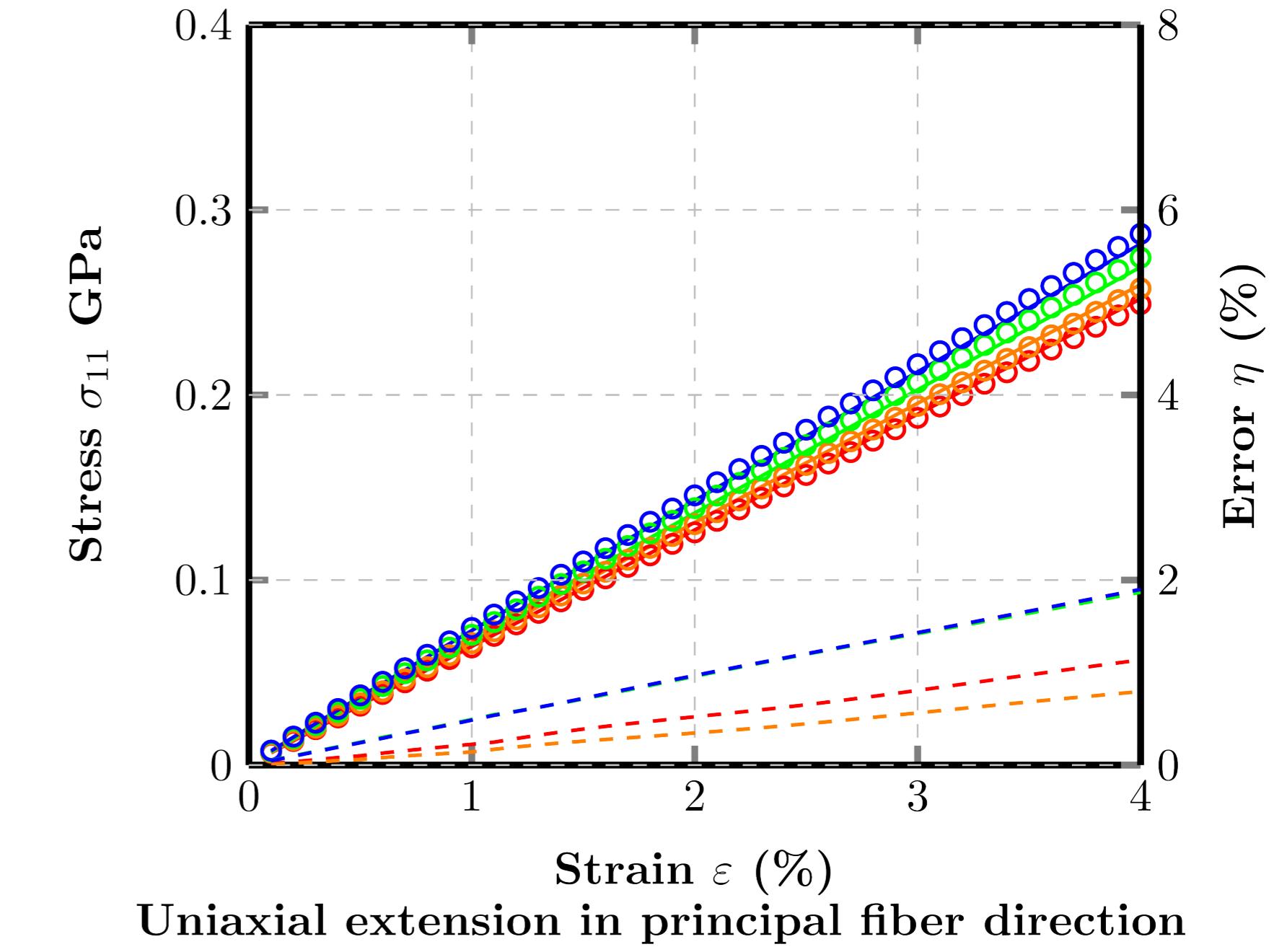


Time & Jobs
data 11.25 hours
threads 48
Jobs 5 batch
Training 1.5 hours
threads 1

## Results and Takeaways

- Inelastic error,  $\eta(t) < 2\%$ .
- DMN speed  $< 100$  sec with 1 thread.
- Full field FFT  $\sim 51$  hours with 24 threads.
- For viscoelasticity, total speed-up factor of 44064.
- Achieved 8 layered DMN with state-of-the-art speeds and accuracies.

—  $\dot{\varepsilon} = 0.0005$  —  $\dot{\varepsilon} = 0.005$  —  $\dot{\varepsilon} = 0.05$  —  $\dot{\varepsilon} = 0.5$



## Contact

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## References

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- [2] Z. Liu and C. Wu, "Exploring the 3d architectures of deep material network in data-driven multiscale mechanics," JMPS, vol. 127, pp. 20–46, 2019.
- [3] S. Gajek, M. Schneider, and T. Böhlke, "An FE-DMN method for the multiscale analysis of short fiber reinforced plastic components," CMAME, vol. 384, p. 113952, 2021.
- [4] A. P. Dey, F. Welschinger, M. Schneider, S. Gajek, and T. Böhlke, "Training deep material networks to reproduce creep loading of short fiber-reinforced thermoplastics with an inelastically-informed strategy," AoAM, vol. 92, no. 9, pp. 2733–2755, 2022.
- [5] P. Bhat Keelanje Srinivas, MSc thesis-A data driven efficient multiscale computational tool using hybrid AI modelling framework for short fiber reinforced thermoplastics, University Of Stuttgart, 2022.