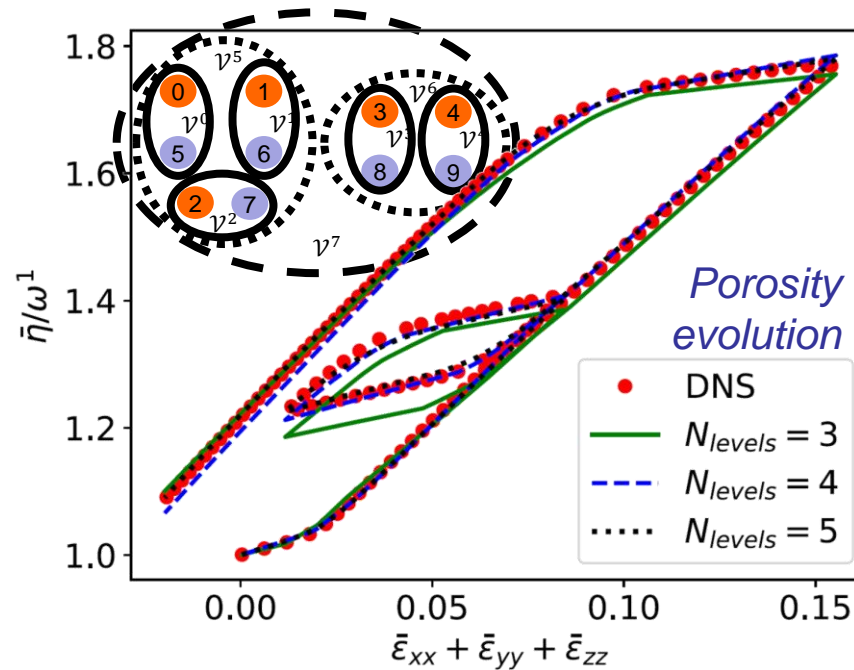




# Redefinition of the interactions in Deep-Material-Networks

Noels Ludovic, Wu Ling, Nguyen Van Dung

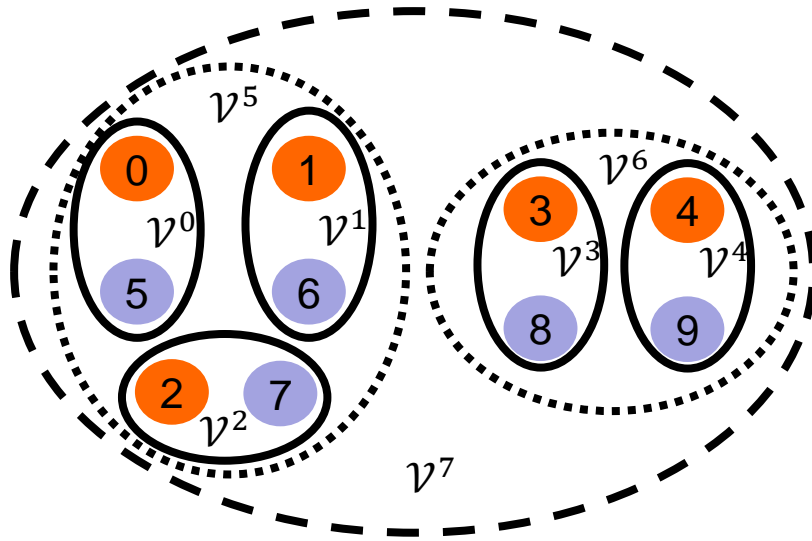


The research has been funded by the FNRS and by Walloon Region under the agreement no.7911-VISCOS in the context of the 21st SKYWIN call.

# Deep Material Networks with laminate building blocks

- Architecture of mechanistic building blocks

- Example for a 2-phase material



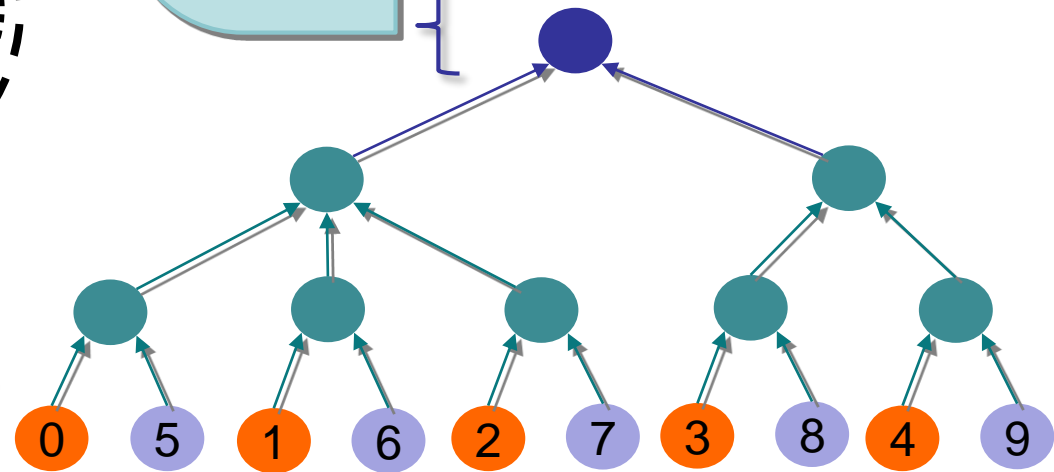
Homogenised behaviour

$$\bar{\mathbf{P}}(t) = \bar{\mathbf{P}}(\bar{\mathbf{F}}(t), z(\tau \leq t))$$

$$\bar{\mathbf{P}}(t) = \sum_{i=0}^9 W^i \mathbf{P}^i(t)$$

$$\bar{\mathbf{F}}(t) = \sum_{i=0}^9 W^i \mathbf{F}^i(t)$$

Weight of node  $i$   
(parameter)



Material node  $i = 0..9$ , of weight  $W^i$

Constitutive behaviours:  $\mathbf{P}^p(t) = \mathbf{P}^p(\mathbf{F}^i(t), z(\tau \leq t))$

if node  $i \in$  phase  $p$  for material  $p=0$  or  $p=1$

Z. Liu, C. Wu, M. Koishi, A deep material network for multiscale topology learning and accelerated nonlinear modeling of heterogeneous materials

# Deep Material Networks with laminate building blocks

- Mechanism  $k = 0..M - 1$

- Link homogenised deformation gradient to node ones

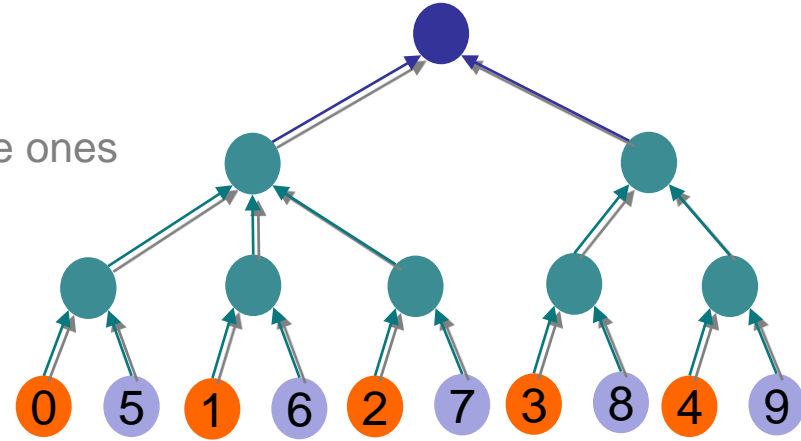
- Construction of a strain fluctuation field

$$\bar{\mathbf{F}} + \sum_{k=0}^{M-1} \alpha^{i,k} \mathbf{a}^k \otimes \mathbf{G}^k = \mathbf{F}^i, \quad i = 0..9$$

Contribution of node  $i$  in mechanism  $k$  (parameter?)

Direction of mechanism  $k$  (parameter)

Degrees of freedom of mechanism  $k$  defining the strain fluctuation



Weight of node  $i$  (parameter)

- Constraints from strain averaging

- $\bar{\mathbf{F}} = \sum_i W^i \mathbf{F}^i \Rightarrow \sum_k \left( \sum_i W^i \alpha^{i,k} \right) \mathbf{a}^k \otimes \mathbf{G}^k = 0 \Rightarrow \sum_i W^i \alpha^{i,k} = 0$

- Weak form from Hill-Mandel

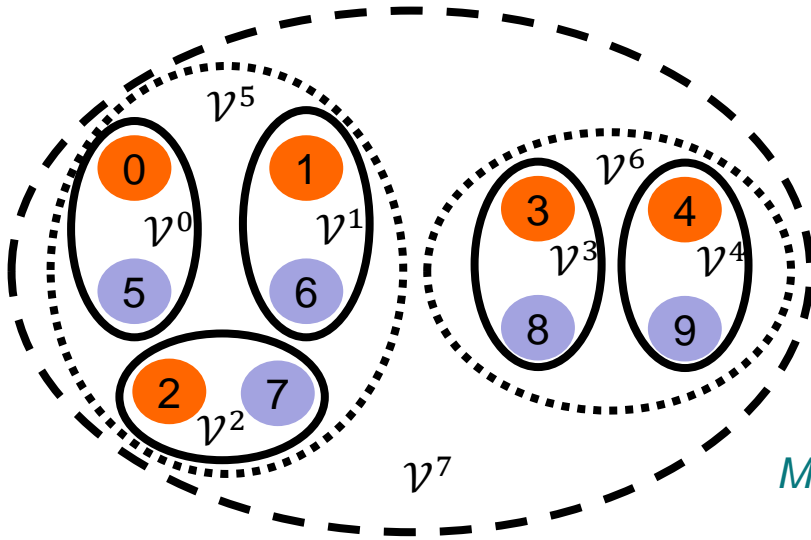
- $\bar{\mathbf{P}} : \delta \bar{\mathbf{F}} = \sum_i W^i \mathbf{P}^i : \delta \mathbf{F}^i \Rightarrow \left[ \sum_k \left( \sum_i W^i \mathbf{P}^i \alpha^{i,k} \right) \cdot \mathbf{G}^k \right] \cdot \delta \mathbf{a}^k = 0$

# Deep Material Networks with laminate building blocks

- Mechanistic building blocks: Laminate

Z. Liu, C. Wu, M. Koishi, A deep material network for ...

- Interaction  $\mathcal{V}^j$  as a laminate



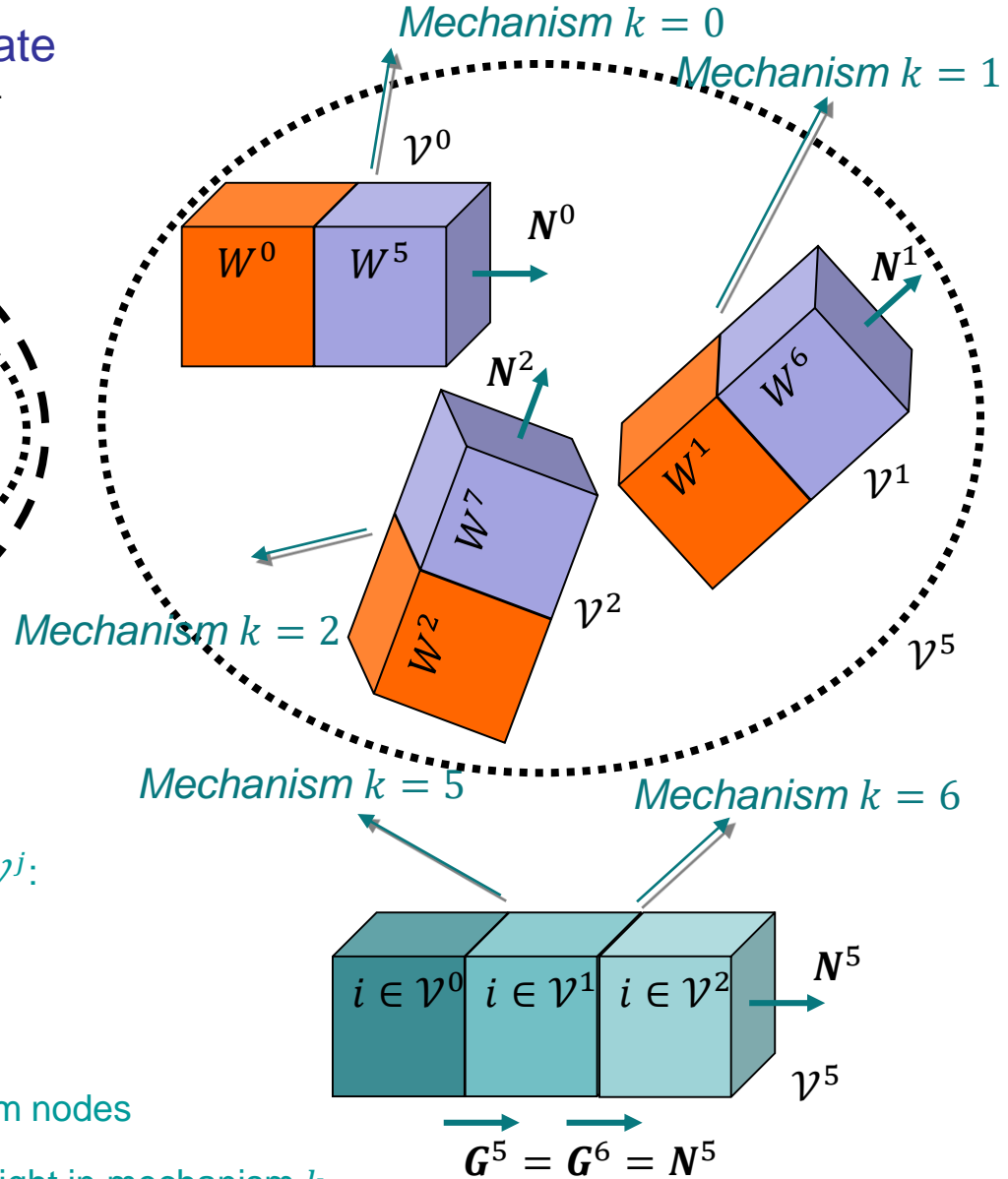
- Parameters

- Weight:  $W^i, i = 0..9$
- Unique direction for an interaction  $\mathcal{V}^j$ :

$$\mathbf{G}^k \Rightarrow \mathbf{N}^j, j = 0..7$$

- Constraint

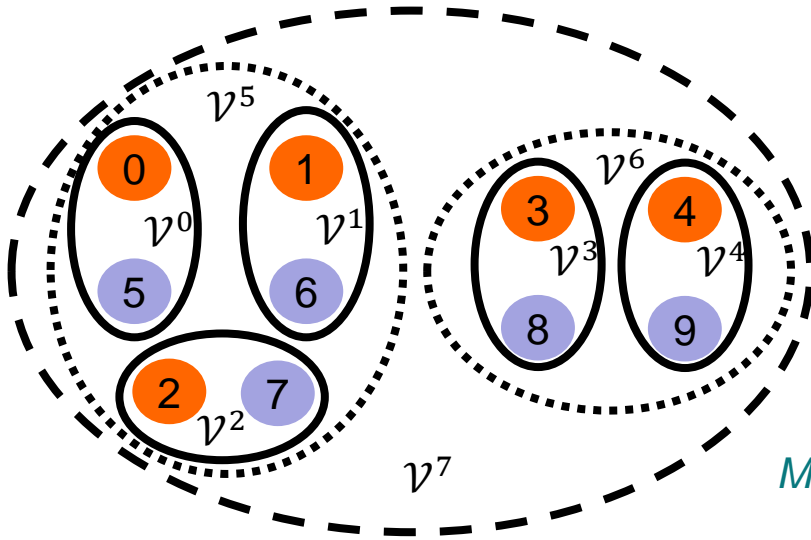
- $\sum_i W^i \alpha^{i,k} = 0 \Rightarrow \alpha^{i,k}$  from nodes  
weight in mechanism  $k$



# Deep Material Networks with laminate building blocks

- Mechanistic building blocks: Laminate

- Interaction  $\mathcal{V}^j$  as a laminate

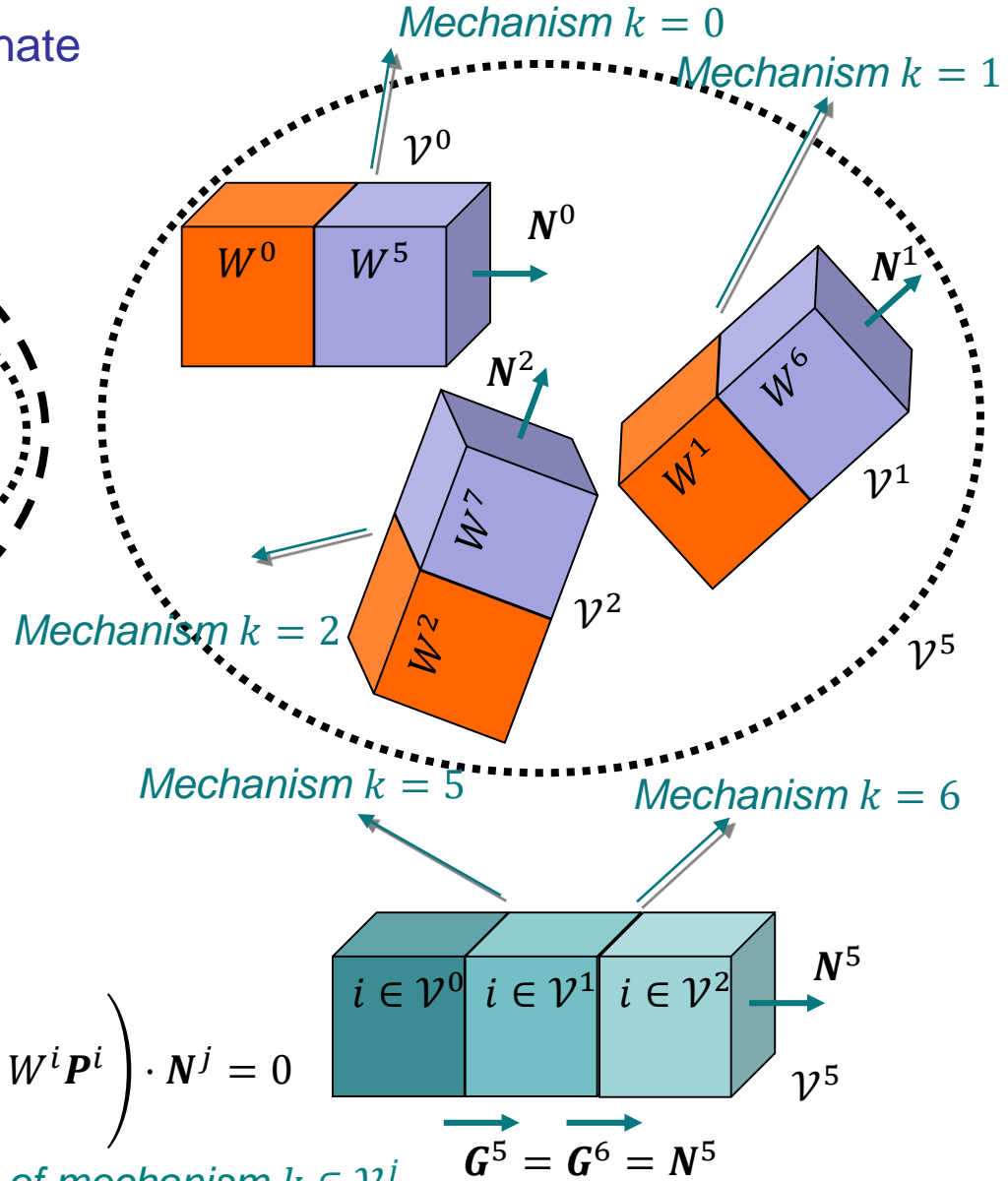


- Weak form

$$\left[ \sum_k \left( \sum_i W^i \mathbf{P}^i \alpha^{i,k} \right) \cdot \mathbf{G}^k \right] \cdot \delta \mathbf{a}^k = 0$$

$$\Rightarrow \left( \frac{1}{W(\mathcal{V}^m)} \sum_{i \in \mathcal{V}^m} W^i \mathbf{P}^i - \frac{1}{W(\mathcal{V}^{m+1})} \sum_{i \in \mathcal{V}^{m+1}} W^i \mathbf{P}^i \right) \cdot \mathbf{N}^j = 0$$

$j = 0..7, \mathcal{V}^m$  and  $\mathcal{V}^{m+1}$  interactions of mechanism  $k \in \mathcal{V}^j$



# Deep Material Networks with laminate building blocks

- Offline stage on a  $p$ -phase RVE

- Topological parameters  $\chi$

- Weight:  $W^i, i = 0..9$

- Direction of interaction  $\nu^j: N^j, j = 0..7$

$$\chi = [W^0, \dots, W^9, N^0, \dots, N^7]$$

- Using elastic data

- Random properties on RVE

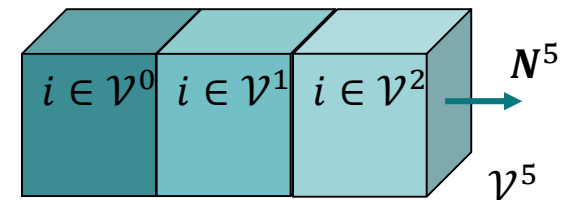
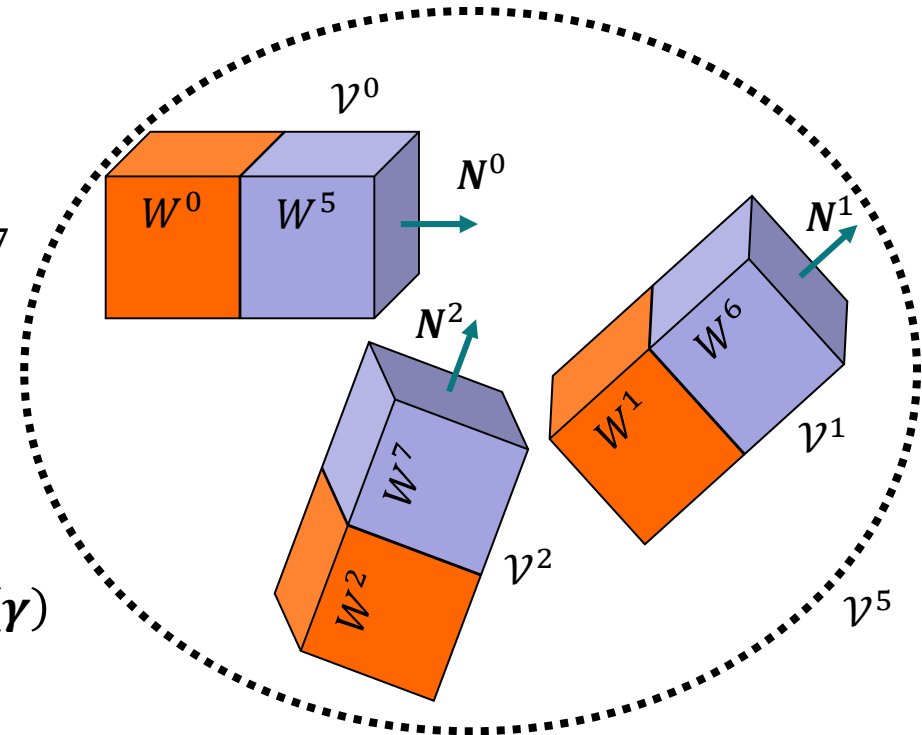
$$\gamma = [E_0, \nu_0, E_1, \nu_1 \dots E_p, \nu_p, ]$$

➡ Direct simulations on RVE ➡  $\hat{\mathbb{C}}(\gamma)$

- Cost functions to minimise

$$L(\hat{\mathbb{C}}, \bar{\mathbb{C}}(\chi)) = \frac{1}{n} \sum_{s=1}^n \frac{\|\hat{\mathbb{C}}(\gamma_s) - \bar{\mathbb{C}}(\chi|\gamma_s)\|}{\|\hat{\mathbb{C}}(\gamma_s)\|}$$

- « Stochastic gradient descent (SGD) » algorithm

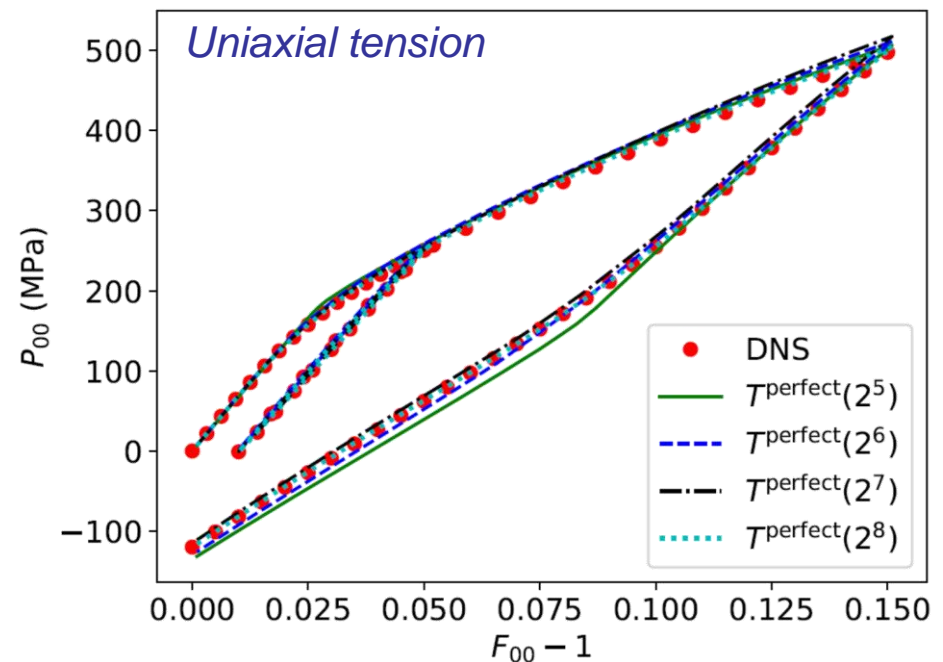
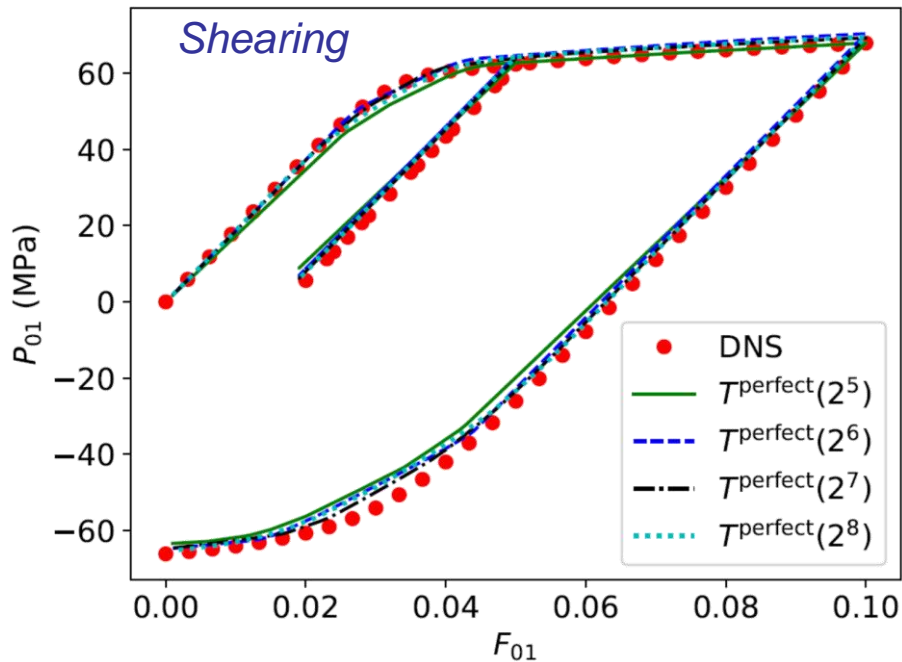
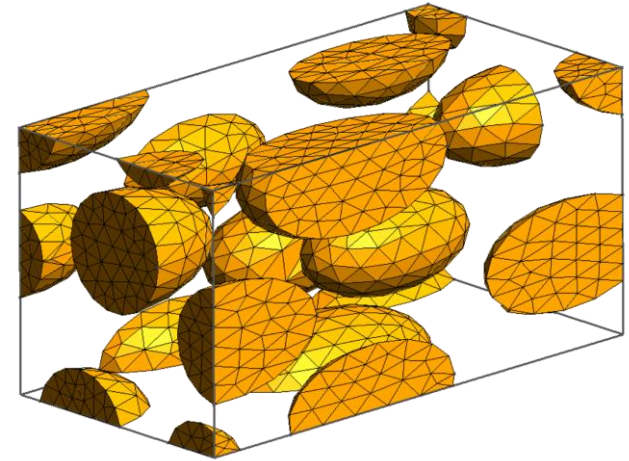


# Deep Material Networks with laminate building blocks

- Online stage on a particle-reinforced composite

- Properties

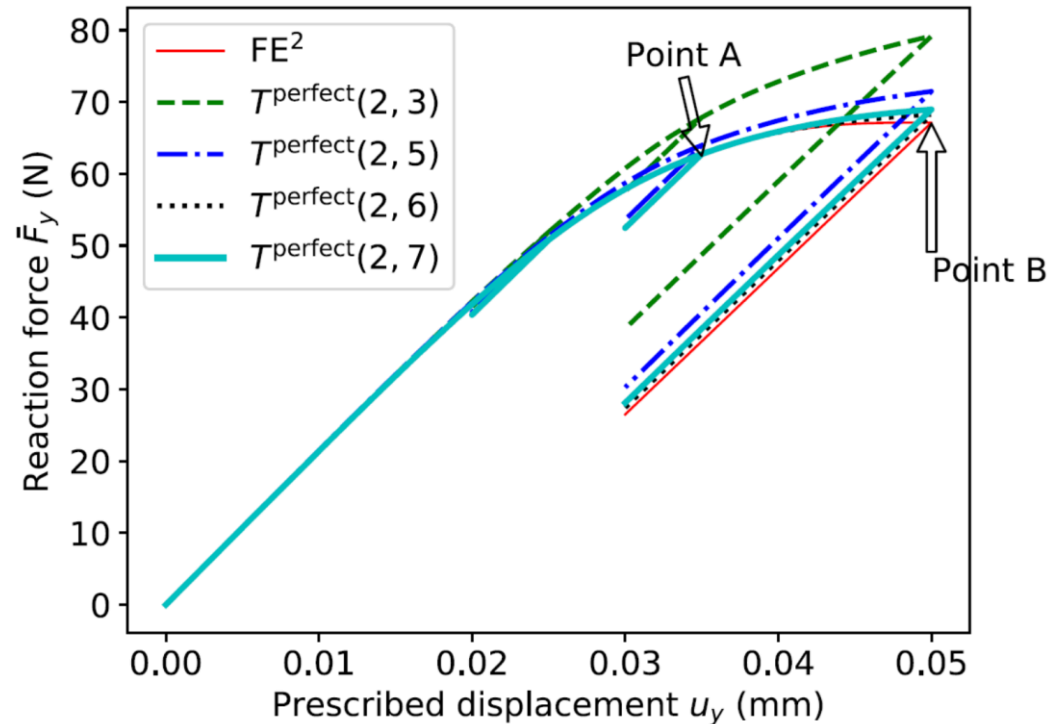
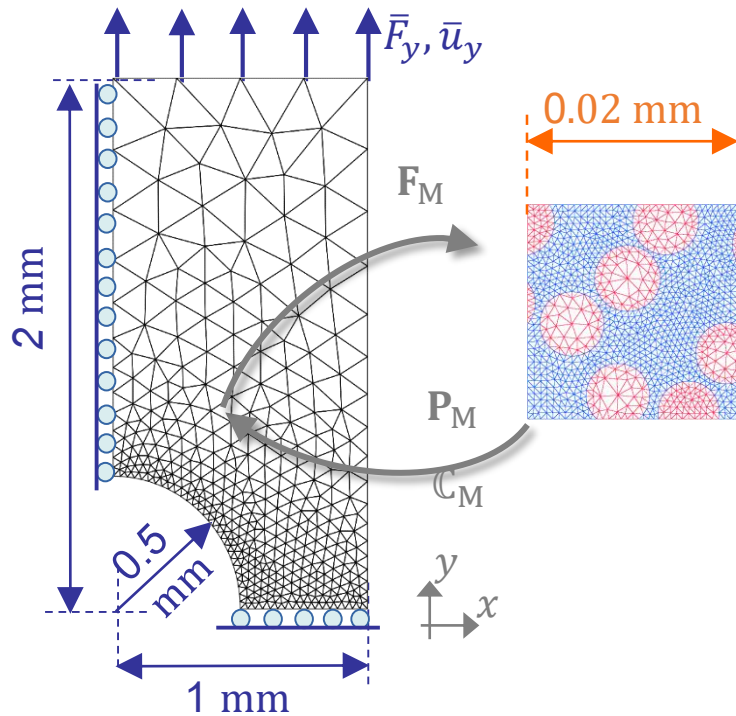
- Elastic inclusions
- Elasto-plastic matrix



# Deep Material Networks with laminate building blocks

- Multiscale simulation
  - Elasto-plastic composite RVE
  - Comparison FE<sup>2</sup> vs. DMN-surrogate

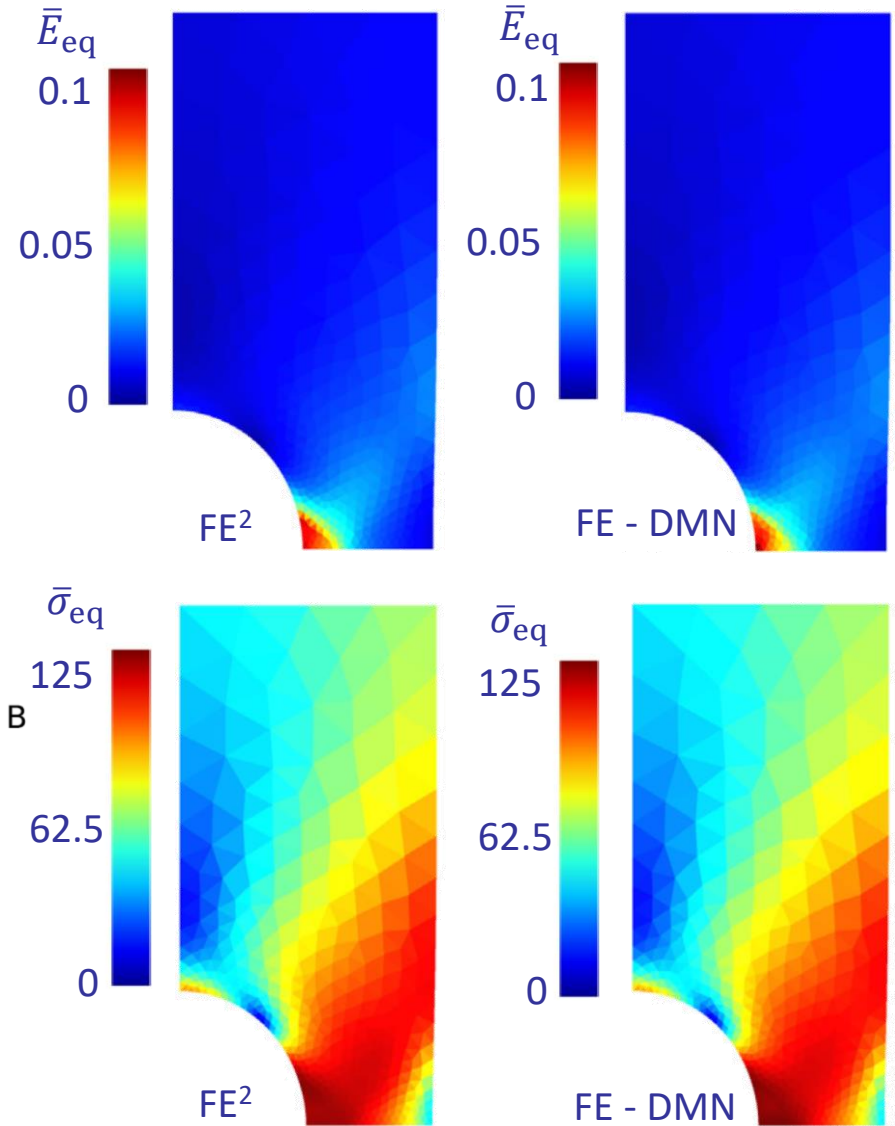
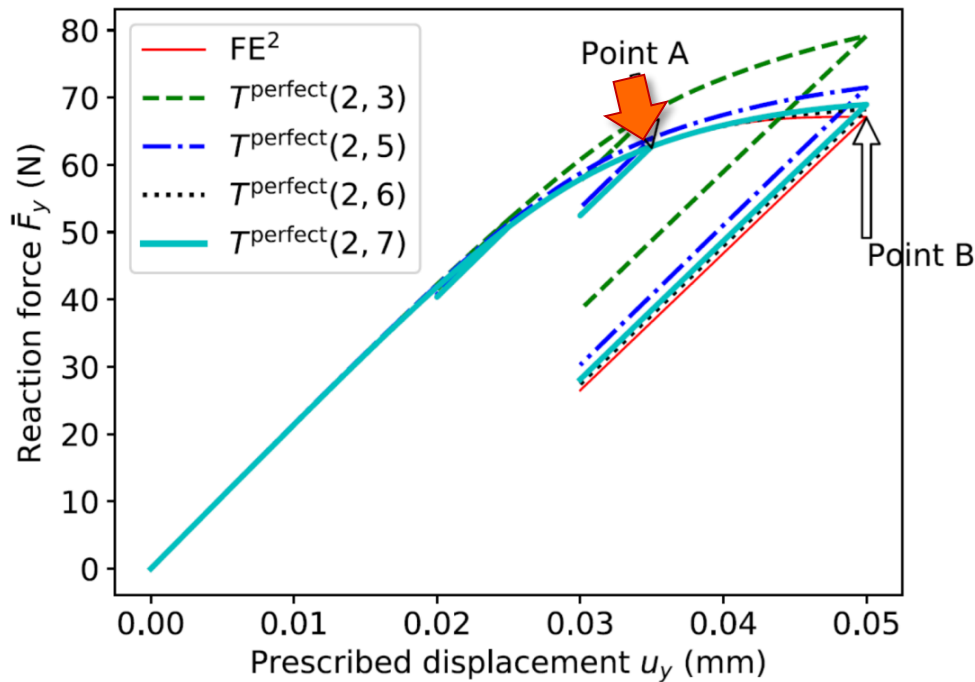
Off-line	FE <sup>2</sup>	FE-DMN
Data generation	-	10 min.-cpu
Training	-	2 min.-cpu
On-line	FE <sup>2</sup>	FE-DMN
Simulation	18000 h-cpu	½ to 34 h-cpu





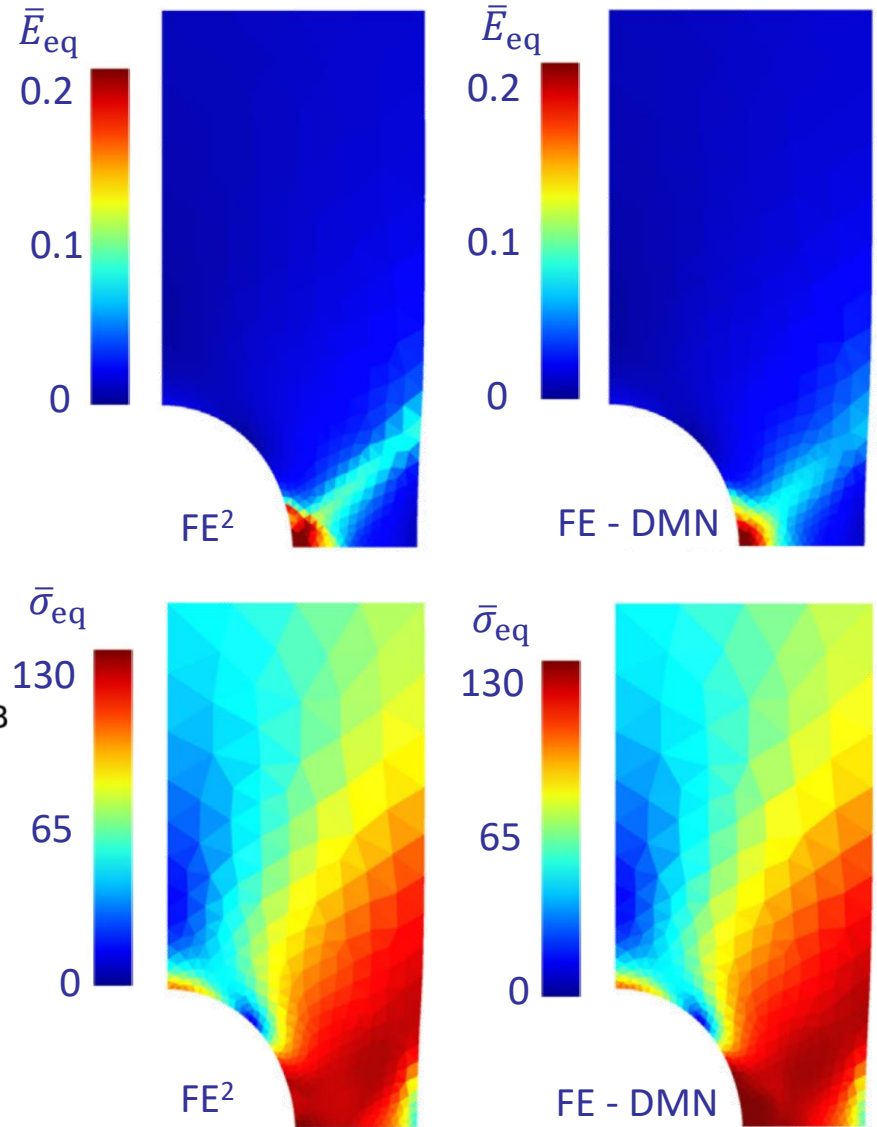
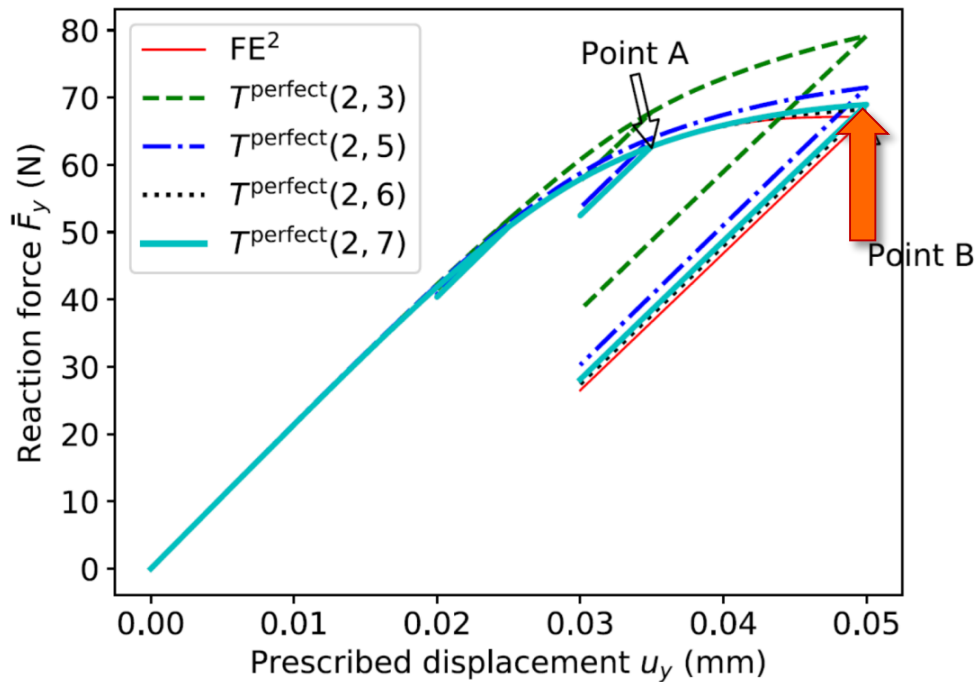
# Deep Material Networks with laminate building blocks

- Multiscale simulation
  - Stress-strain distribution at point A
  - For  $2^7$  material nodes



# Deep Material Networks with laminate building blocks

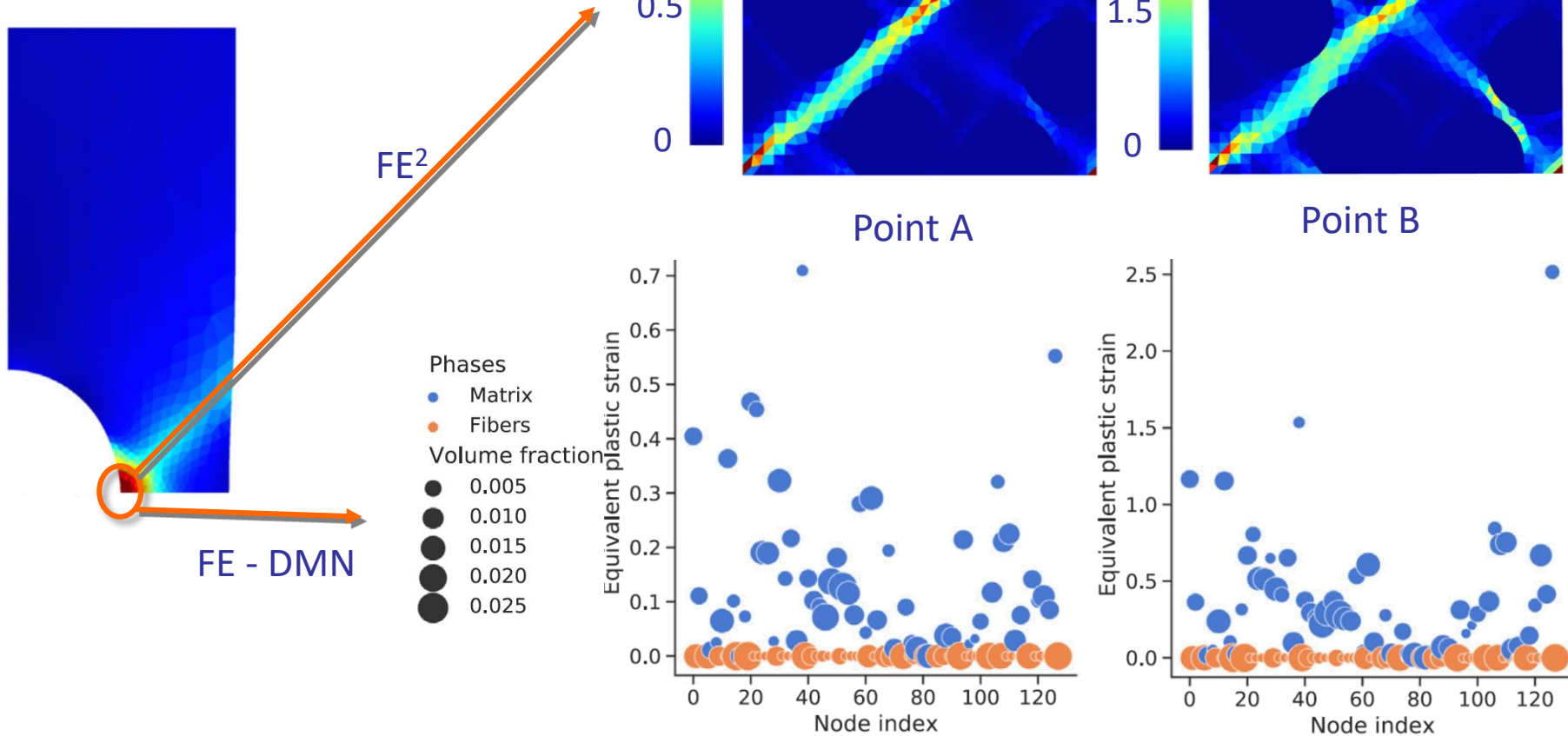
- Multiscale simulation
  - Stress-strain distribution at point B
  - For  $2^7$  material nodes



# Deep Material Networks with laminate building blocks

- Multiscale simulation

- Localisation step
- For  $2^7$  material nodes



# Deep Material Networks from the interactions viewpoint

- Alternative to laminate (e.g. for porous material)
- Mechanism  $j = 0..M - 1$  of interaction  $\nu^j$ 
  - Homogenised deformation gradient

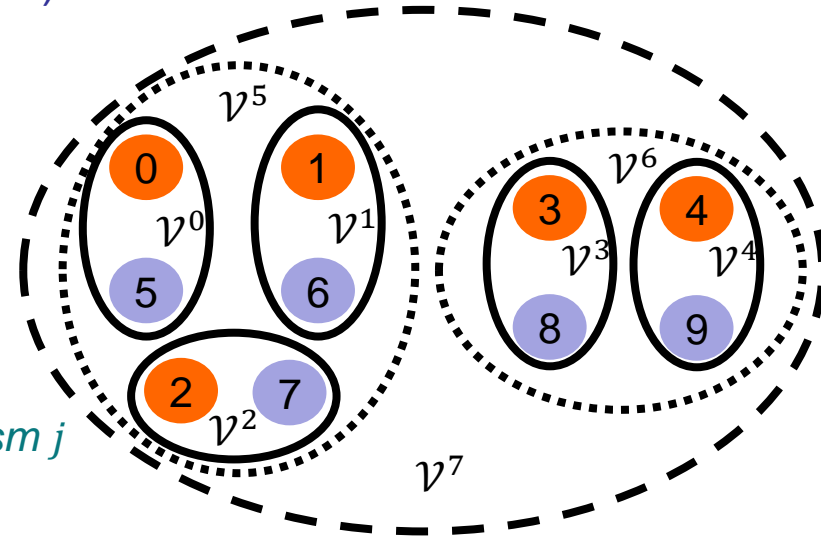
- Construction of a strain fluctuation field

$$\bar{\mathbf{F}} + \sum_{j:i \in \mathcal{V}^j} \alpha^{i,j} \mathbf{a}^j \otimes \mathbf{N}^j = \mathbf{F}^i, \quad j = 0..M - 1$$

Contribution of node  $i$  in mechanism  $j$  (parameter?)

Degrees of freedom of mechanism  $j$  defining the strain fluctuation

Direction of mechanism  $j$  (parameter)



Weight of node  $i$  (parameter)

- Constraints from strain averaging

$$\bar{\mathbf{F}} = \sum_i W^i \mathbf{F}^i \quad \Rightarrow \quad \sum_j \left( \sum_{i \in \mathcal{V}^j} W^i \alpha^{i,j} \right) \mathbf{a}^j \otimes \mathbf{N}^j = 0 \quad \Rightarrow \quad \sum_{i \in \mathcal{V}^j} W^i \alpha^{i,j} = 0$$

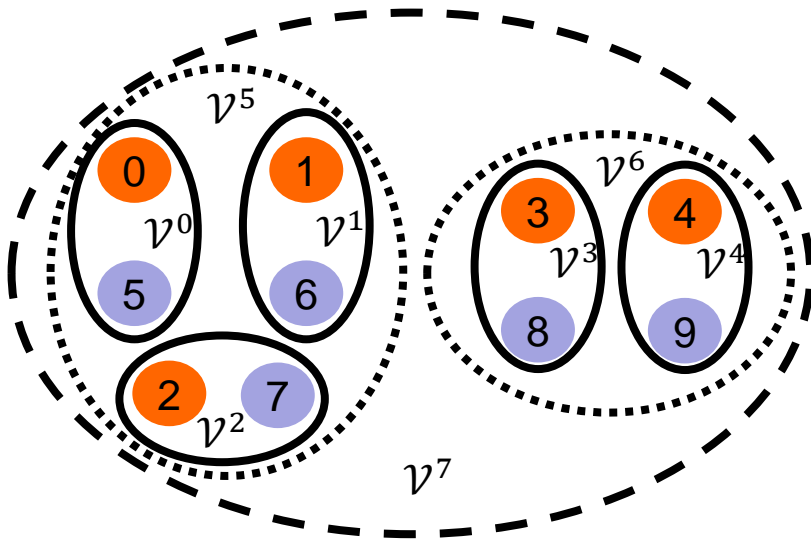
- Weak form from Hill-Mandel

$$\bar{\mathbf{P}} : \delta \bar{\mathbf{F}} = \sum_i W^i \mathbf{P}^i : \delta \mathbf{F}^i \quad \Rightarrow \quad \left[ \sum_j \left( \sum_{i \in \mathcal{V}^j} W^i \mathbf{P}^i \alpha^{i,j} \right) \cdot \mathbf{N}^j \right] \cdot \delta \mathbf{a}^j = 0$$

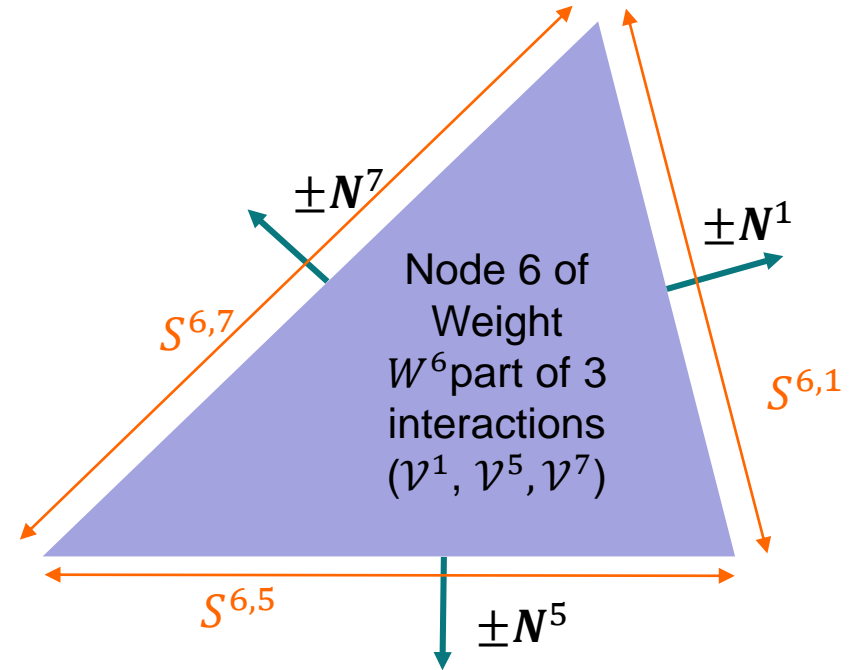
# Deep Material Networks from the interactions viewpoint

- Mechanistic building blocks: Polyhedra

- Interaction  $\mathcal{V}^j$ ,  $j = 0..M - 1$



- Fluctuation field



- Integration by parts on a polyhedron of volume  $V^i$  associated to node  $i$

$$\bar{\mathbf{F}} + \frac{1}{V^i} \int_{V^i} \mathbf{w} \otimes \nabla dV = \mathbf{F}^i \quad \Rightarrow \quad \bar{\mathbf{F}} + \sum_{j:i \in \mathcal{V}^j} \frac{S^{i,j}}{V^i} \mathbf{w} \otimes (\pm \mathbf{N}^j) = \mathbf{F}^i$$

- To be compared with the interactions

$$\bar{\mathbf{F}} + \sum_{j:i \in \mathcal{V}^j} \alpha^{i,j} \mathbf{a}^j \otimes \mathbf{N}^j = \mathbf{F}^i, \quad j = 0..M - 1$$

- $\alpha^{i,j}$  is the weighted surface of a polyhedron face (parameter to be identified)
- $\mathbf{N}^j$  is the inward or outward normal of the polyhedron face (parameter to be identified)
- $\mathbf{a}^j$  is the fluctuation field (degree of freedom for online simulations)

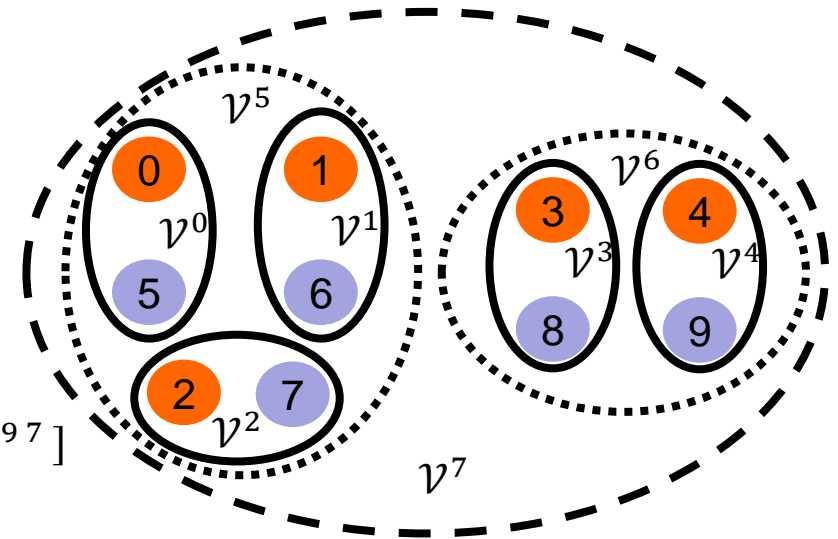
# Deep Material Networks from the interactions viewpoint

- Offline stage on a  $p$ -phase RVE

- Topological parameters  $\chi$

- Nodal weight:  $W^i, i = 0..9$
- Direction of interaction  $\nu^j$ :  $N^j, j = 0..7$
- Interaction weight:  $\alpha^{i,j}$

$$\chi = [W^0, \dots, W^9, N^0, \dots, N^7, \alpha^{0,0}, \dots, \alpha^{9,7}]$$



- Using elastic data

- Random properties on RVE  $\Rightarrow \hat{\mathbb{C}}(\boldsymbol{\gamma})$

$$\boldsymbol{\gamma} = [E_0, \nu_0, E_1, \nu_1 \dots E_p, \nu_p]$$

- Cost functions to minimise  $L(\hat{\mathbb{C}}, \mathbb{C}(\boldsymbol{\chi})) = \frac{1}{n} \sum_{s=1}^n \frac{\|\hat{\mathbb{C}}(\boldsymbol{\gamma}_s) - \bar{\mathbb{C}}(\boldsymbol{\chi}|\boldsymbol{\gamma}_s)\|}{\|\hat{\mathbb{C}}(\boldsymbol{\gamma}_s)\|}$

- Using non-linear response

- Random loading on RVE (strain sequence  $\bar{\mathbf{F}}_s$ )
- Compare stress history  $\mathbf{P}(\bar{\mathbf{F}}_s)$  and quantity of interest  $Z(\bar{\mathbf{F}}_s)$  (e.g. porosity)

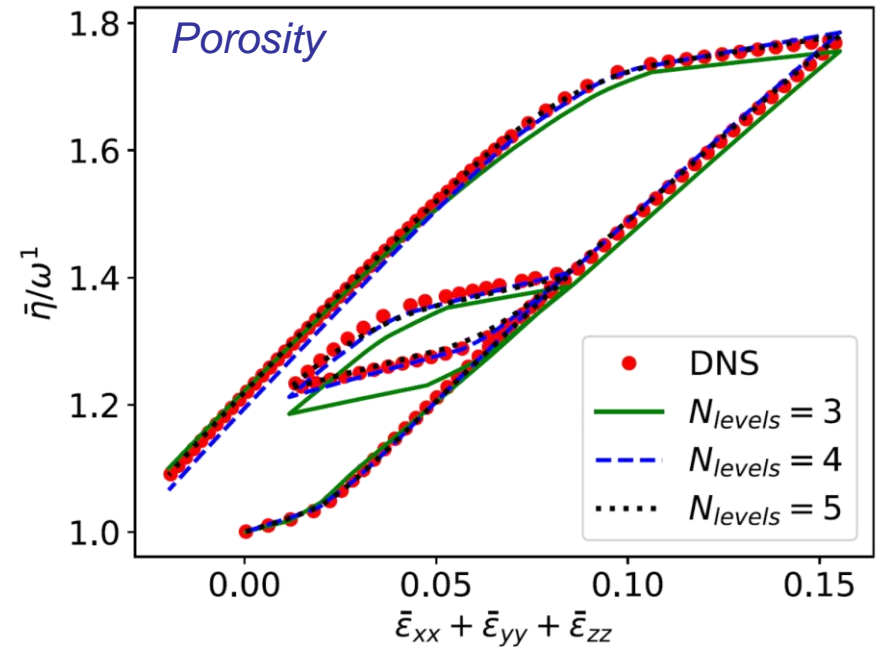
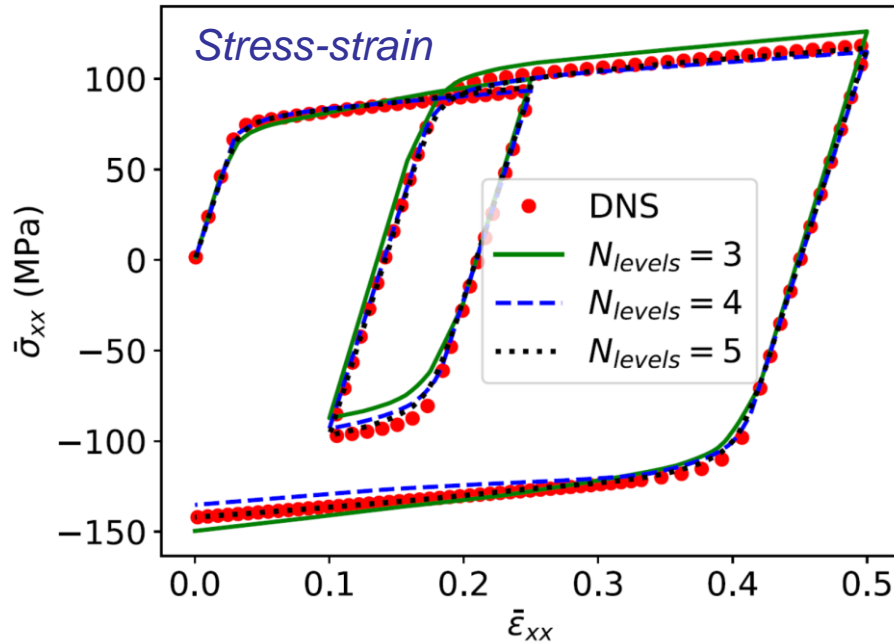
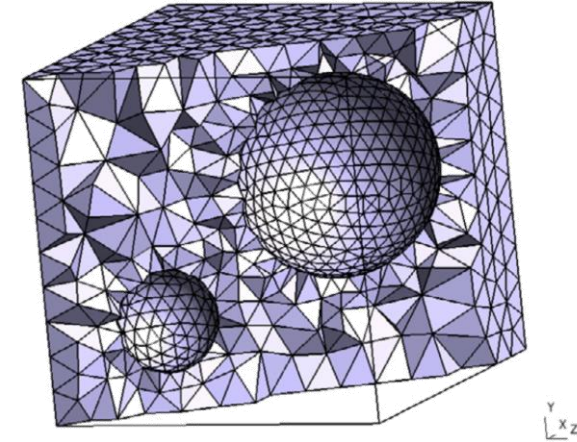
- Cost function to minimise  $L(\hat{\mathbf{P}}, \mathbf{P}(\boldsymbol{\chi})) = \frac{1}{n} \sum_{s=1}^n \frac{\|\hat{\mathbf{P}}(\bar{\mathbf{F}}_s) - \bar{\mathbf{P}}(\boldsymbol{\chi}|\bar{\mathbf{F}}_s)\|}{\|\hat{\mathbf{P}}(\bar{\mathbf{F}}_s)\|} + \frac{1}{n} \sum_{s=1}^n \frac{\|\hat{Z}(\bar{\mathbf{F}}_s) - \bar{Z}(\boldsymbol{\chi}|\bar{\mathbf{F}}_s)\|}{\|\hat{Z}(\bar{\mathbf{F}}_s)\|}$

- By « stochastic gradient descent (SGD) » algorithm

# Deep Material Networks from the interactions viewpoint

- Online stage on a porous material

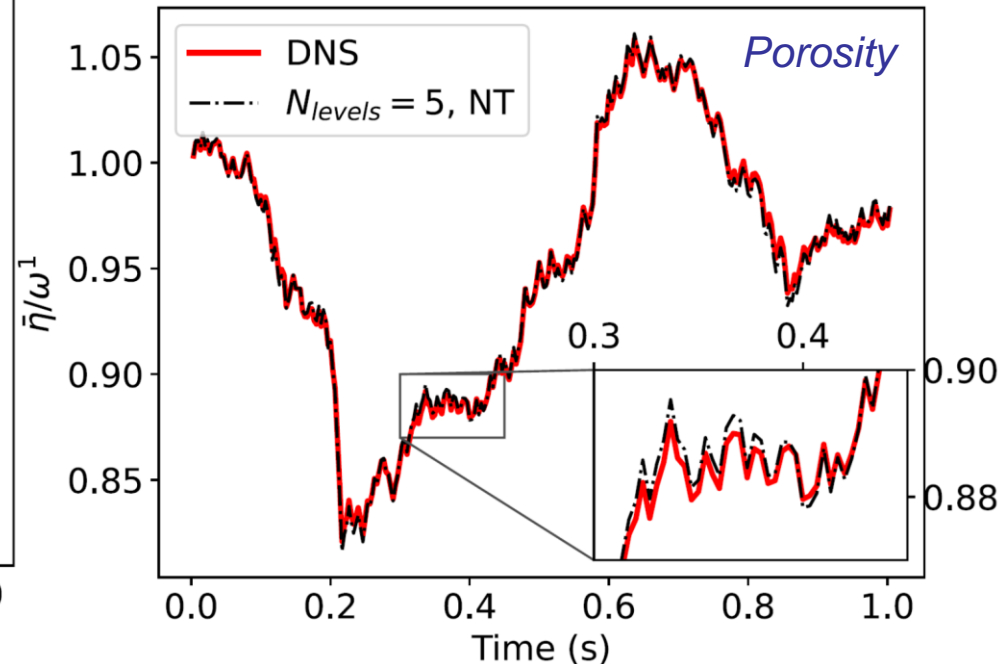
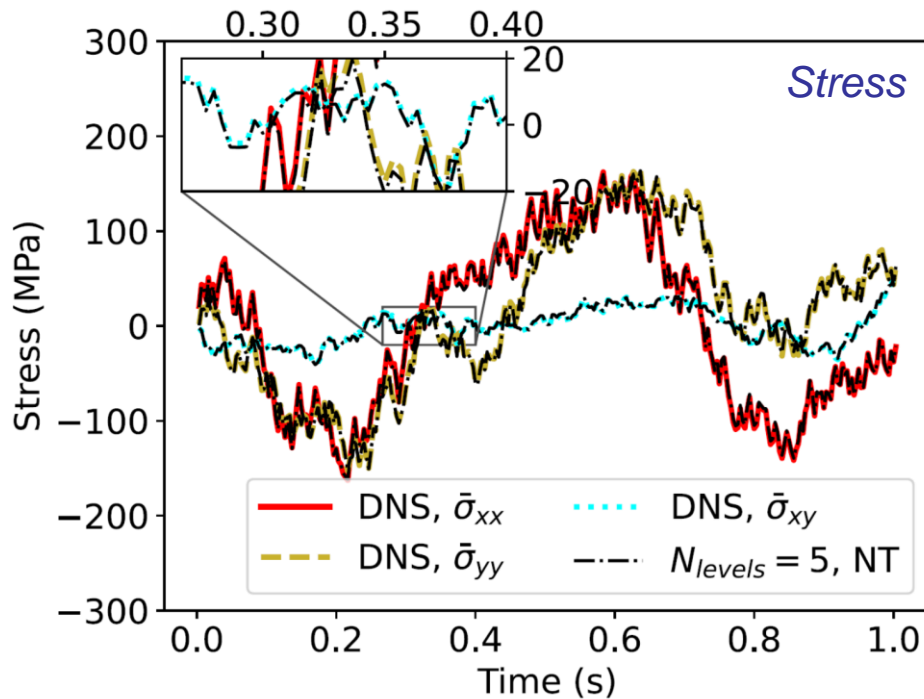
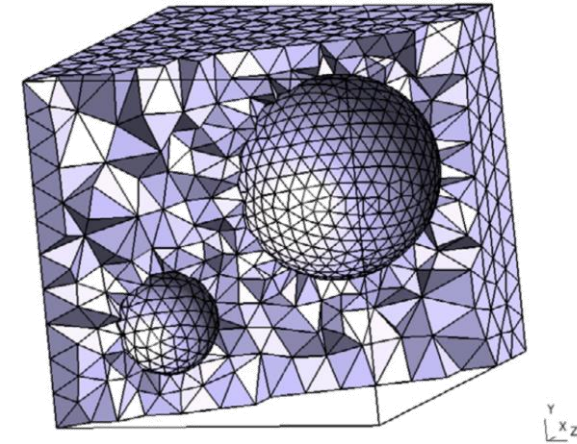
- Properties
  - Elasto-plastic matrix
  - Small strain
- Non-linear training
- Uniaxial tension



# Deep Material Networks from the interactions viewpoint

- Online stage on a porous material

- Properties
  - Elasto-plastic matrix
  - Small strain
- Non-linear training with Material 1, on-line Material 2
- Random loading

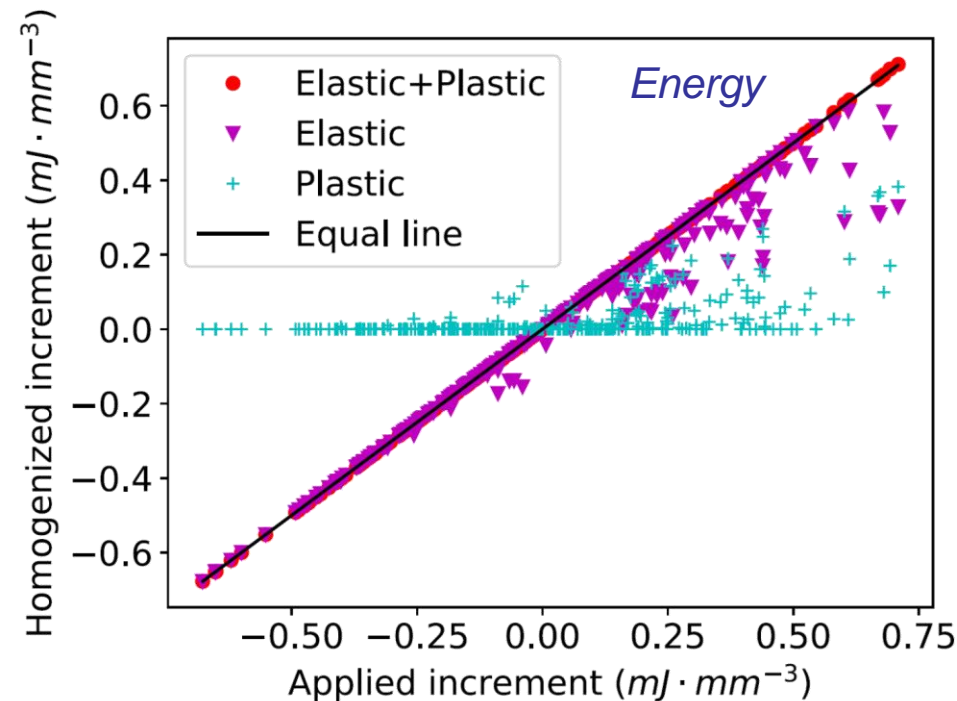
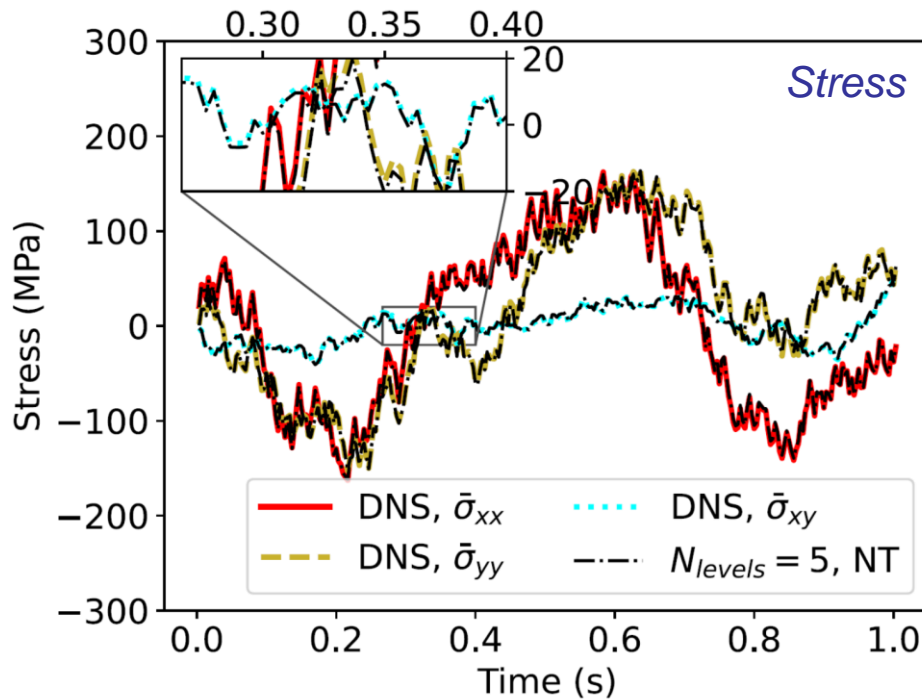
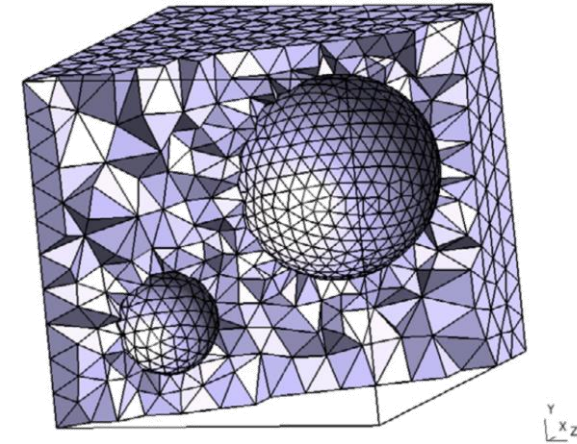




# Deep Material Networks from the interactions viewpoint

- Online stage on a porous material

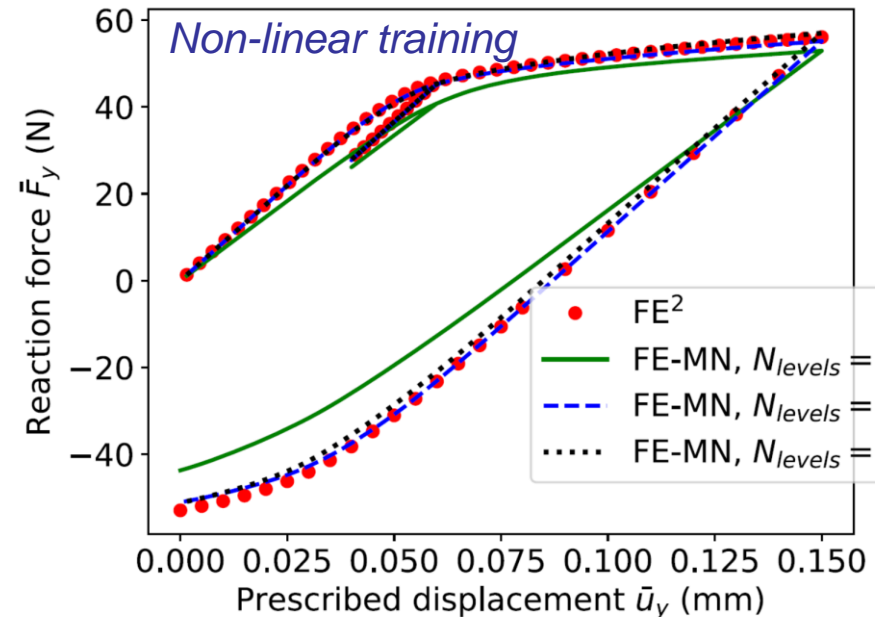
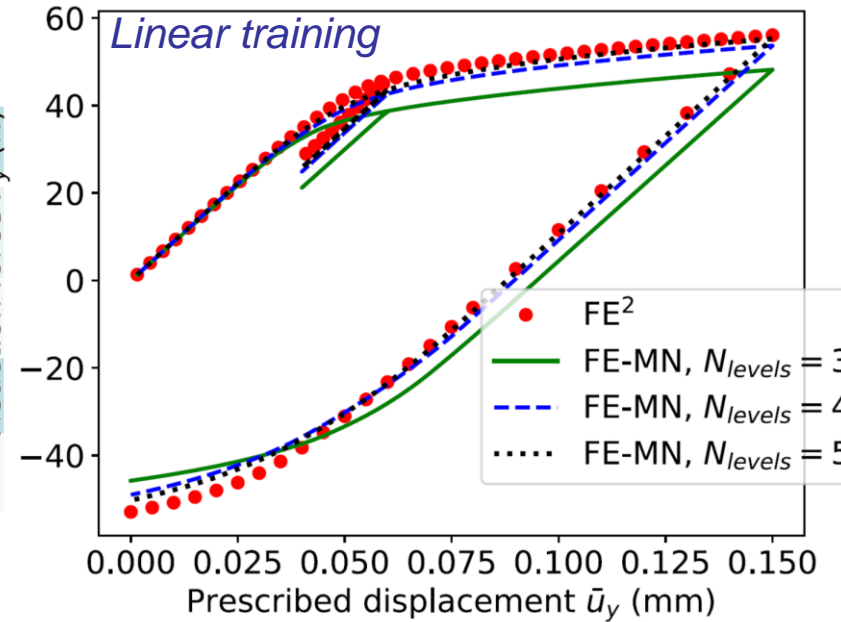
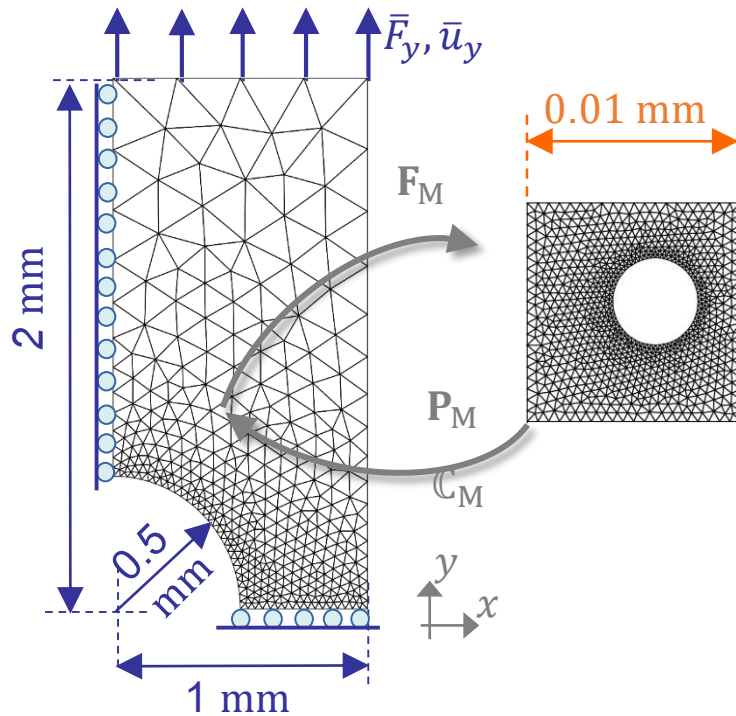
- Properties
  - Elasto-plastic matrix
  - Small strain
- Non-linear training
- Thermodynamically consistent



# Deep Material Networks from the interactions viewpoint

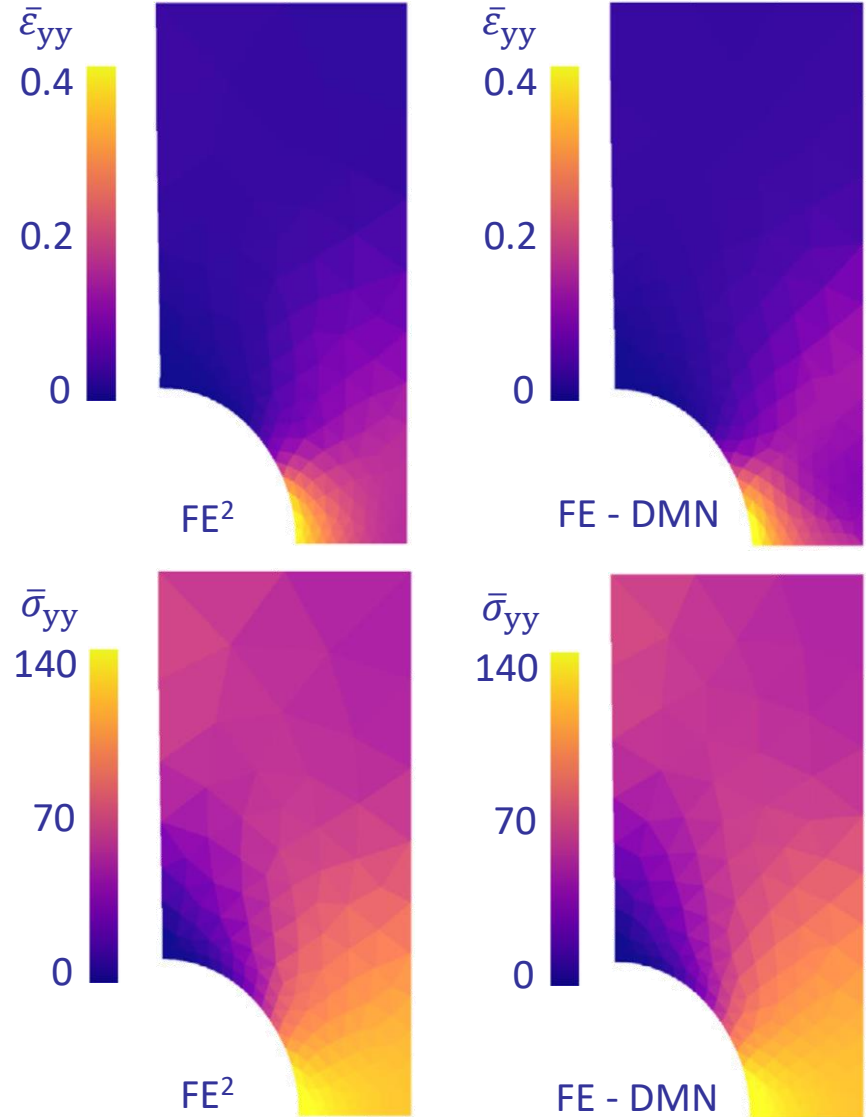
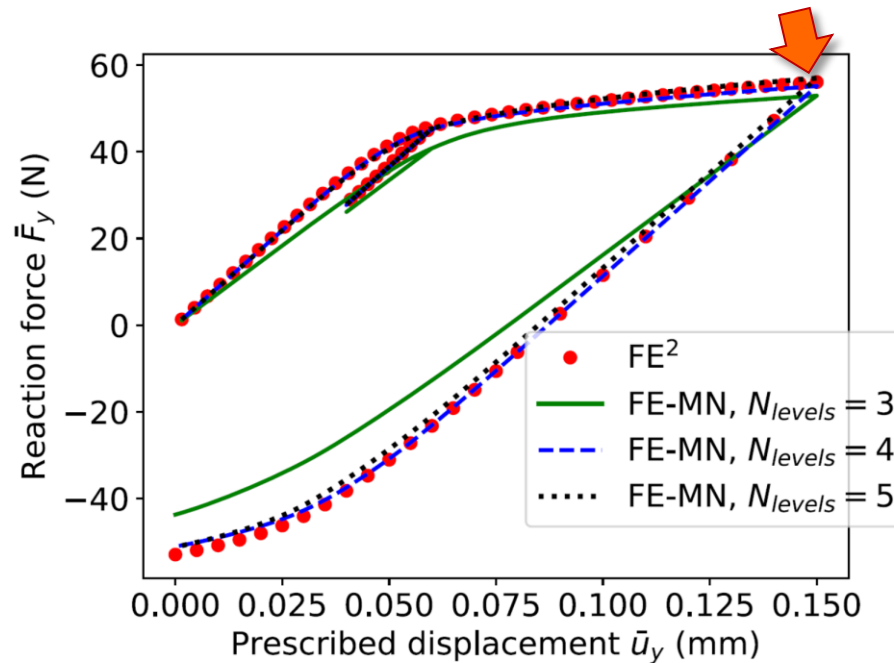
## Multiscale simulation

Off-line	FE <sup>2</sup>	FE-DMN	Reaction force $\bar{F}_y$ (N)
Data generation	-	0.04 (linear) – 3.5 (non-linear) hour.-cpu	
Training	-	0.16-20 hours.-cpu	
On-line	FE <sup>2</sup>	FE-DMN	Reaction force $\bar{F}_y$ (N)
Simulation	7200 h-cpu	0.1 to 1 h-cpu	



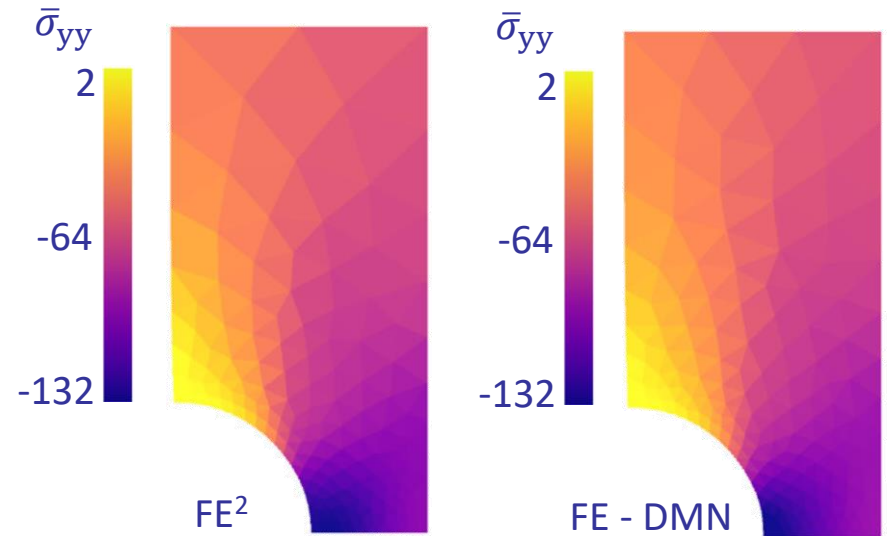
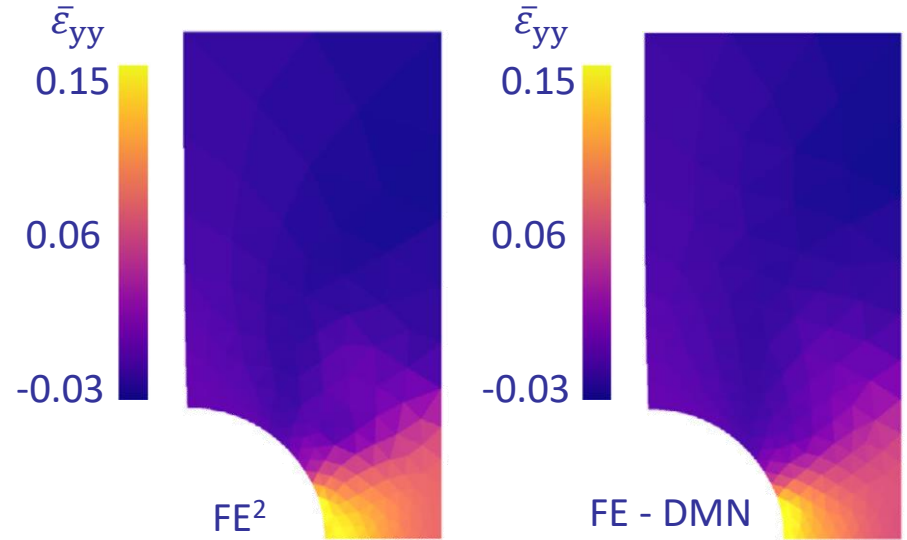
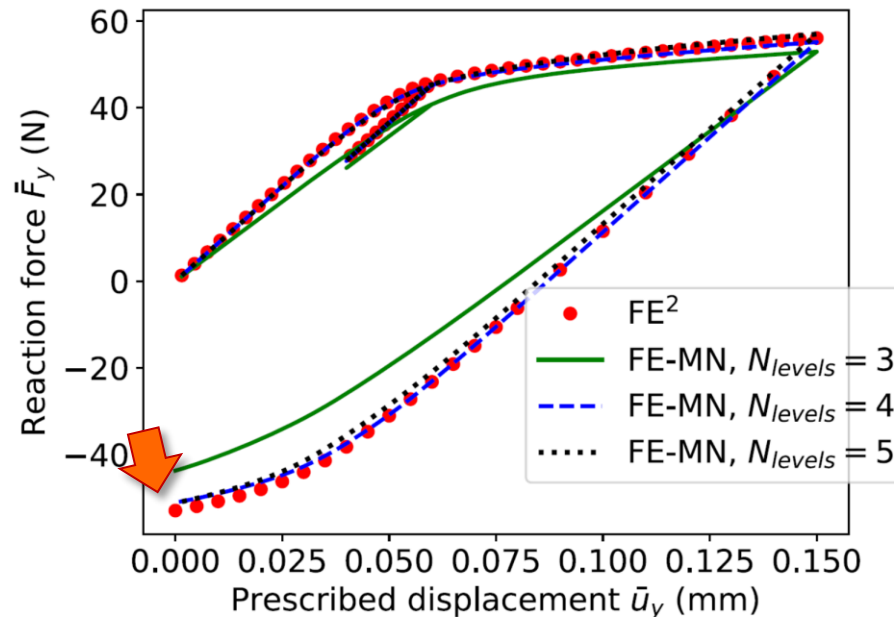
# Deep Material Networks from the interactions viewpoint

- Multiscale simulation
  - Stress-strain distribution at point A
  - For  $2^5$  material nodes
  - Non-linear training



# Deep Material Networks from the interactions viewpoint

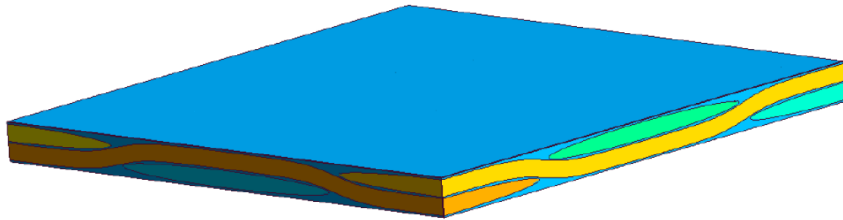
- Multiscale simulation
  - Stress-strain distribution at point B
  - For  $2^5$  material nodes
  - Non-linear training



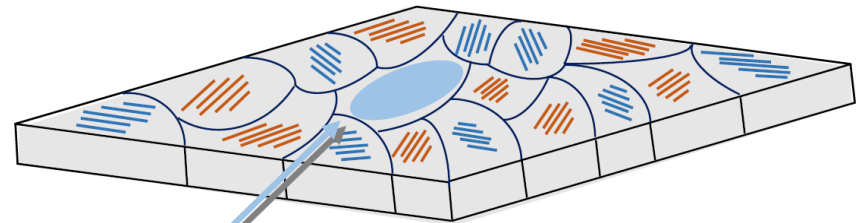
# Mean-Field-Based Deep Material Networks for woven composites

- Definition of 3 Reduced-order-models
- Using simple micro-mechanistic grains
  - MFH (short fibre-reinforced matrix)
  - Voigt mixture
  - Laminate theory

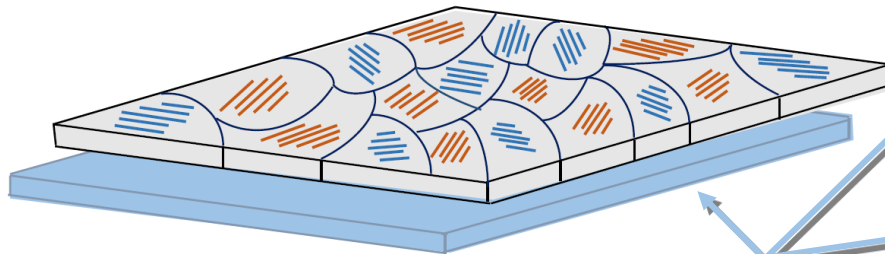
*Elementary cell*



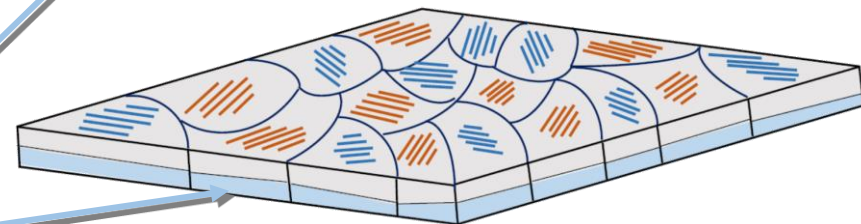
*Voigt – Mean-Field-Homogenization*



*Laminate – Voigt – Mean-Field-Homogenization*



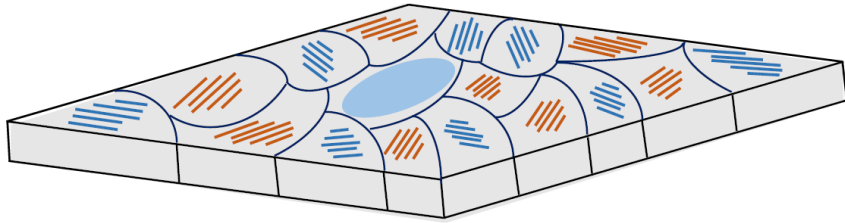
*Voigt – Laminate – Mean-Field-Homogenization*



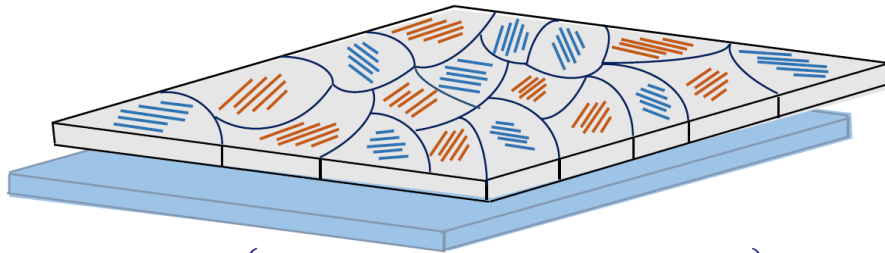
matrix

# Mean-Field-Based Deep Material Networks for woven composites

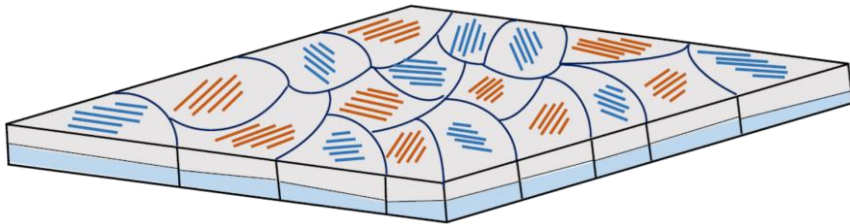
- Definition of material networks



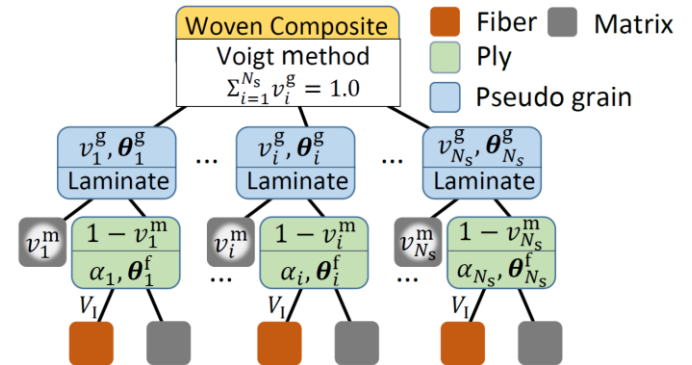
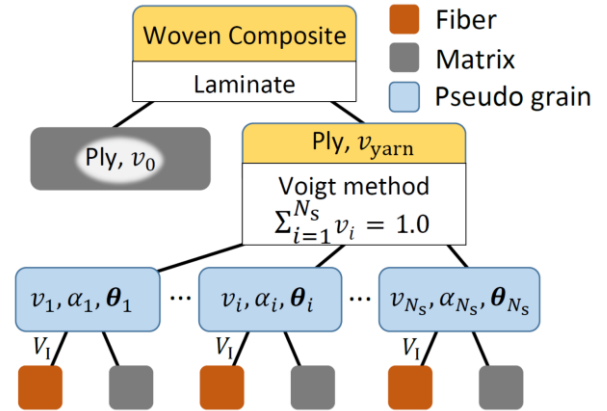
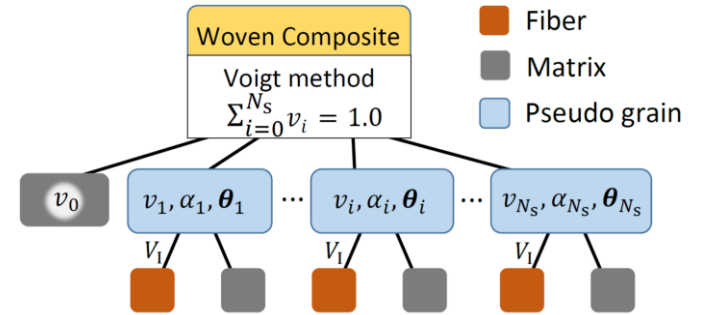
$$\chi^{VM} = \left\{ v_i, \theta_i, \alpha_i \mid i = 1, \dots, N_S; \sum_{i=1}^{N_S} v_i = 1.0 - v_0 \right\}$$



$$\chi^{LVM} = \left\{ v_i, \theta_i, \alpha_i \mid i = 1, \dots, N_S; \sum_{i=1}^{N_S} v_i = 1.0 \right\}$$



$$\chi^{VLM} = \left\{ v_i^g, \theta_i^g, v_i^m, \theta_i^f, \alpha_i \mid i = 1, \dots, N_S; \sum_{i=1}^{N_S} v_i^g = 1.0; \sum_{i=1}^{N_S} v_i^g v_i^m = v_0 \right\}$$



# Mean-Field-Based Deep Material Networks for woven composites

- Identification of topological parameters from direct simulations

- Parameters:

$$\chi^{\text{VM}} = \left\{ v_i, \theta_i, \alpha_i \mid i = 1, \dots, N_S; \sum_{i=1}^{N_S} v_i = 1.0 - v_0 \right\}$$

$$\chi^{\text{LVM}} = \left\{ v_i, \theta_i, \alpha_i \mid i = 1, \dots, N_S; \sum_{i=1}^{N_S} v_i = 1.0 \right\}$$

$$\chi^{\text{VLM}} = \left\{ v_i^g, \theta_i^g, v_i^m, \theta_i^f, \alpha_i \mid i = 1, \dots, N_S; \sum_{i=1}^{N_S} v_i^g = 1.0; \sum_{i=1}^{N_S} v_i^g v_i^m = v_0 \right\}$$

- Using elastic data

- Random properties on RVE

$$\boldsymbol{\gamma} = [E_0, v_0, E_I^T, E_I^L, v_I^{LT}, v_I^{TT}, G_I^{LT}, V_I]$$

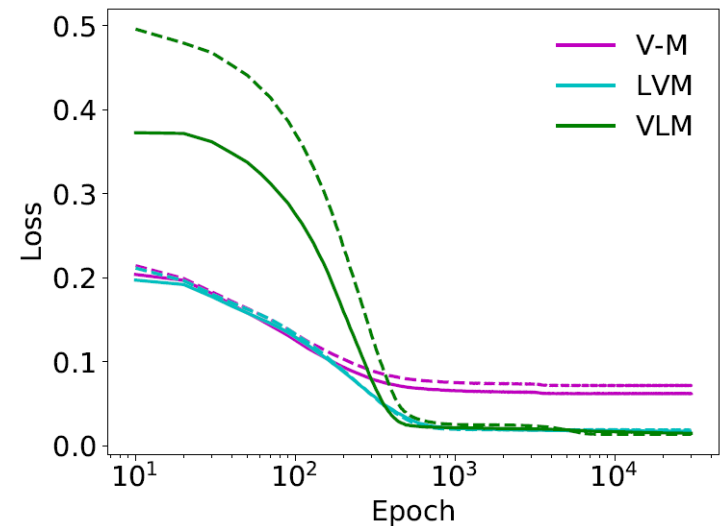
➔ Direct simulations on RVE

- Cost functions to minimise

$$L(\hat{\mathbb{C}}, \mathbb{C}(\boldsymbol{x})) = \frac{1}{n} \sum_{s=1}^n \frac{\|\hat{\mathbb{C}}(\boldsymbol{\gamma}_s) - \mathbb{C}(\boldsymbol{x}|\boldsymbol{\gamma}_s)\|}{\|\hat{\mathbb{C}}(\boldsymbol{\gamma}_s)\|} + \frac{\lambda}{2} G(\boldsymbol{x})$$

- « stochastic gradient descent (SGD) » algorithm

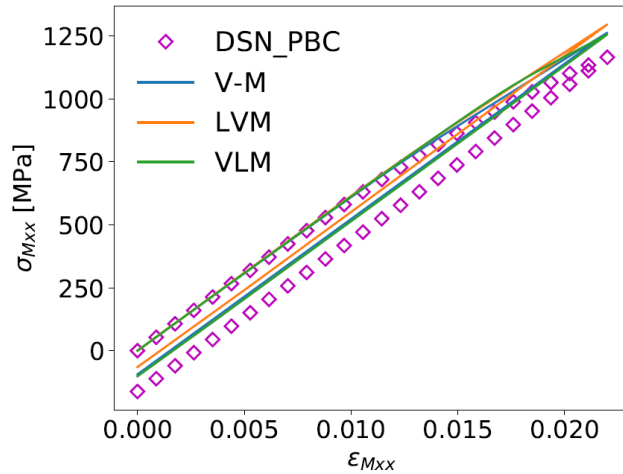
Constraints



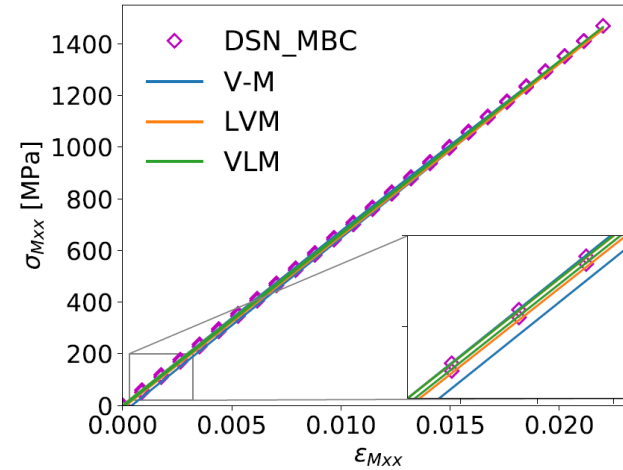
# Mean-Field-Based Deep Material Networks for woven composites

- Elasto-plastic matrix case

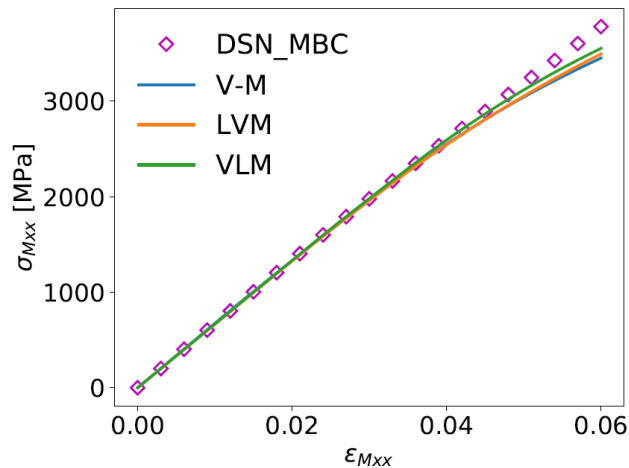
*PBC tension cyclique*



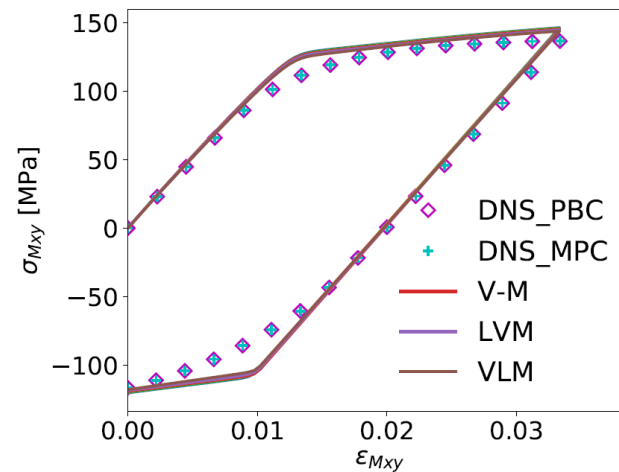
*MBC tension cyclique*



*MBC tension*



*Cisaillement*





- Publications (doi)
  - [10.1016/j.cma.2021.114300](https://doi.org/10.1016/j.cma.2021.114300)
    - [Open data](#)
  - [10.1016/j.euromechsol.2021.104384](https://doi.org/10.1016/j.euromechsol.2021.104384)
    - [Open data](#)
  - [10.1016/j.compstruct.2021.114058](https://doi.org/10.1016/j.compstruct.2021.114058)
    - [Open data](#)