Selective distillation algorithm to evaluate Deep Material Networks

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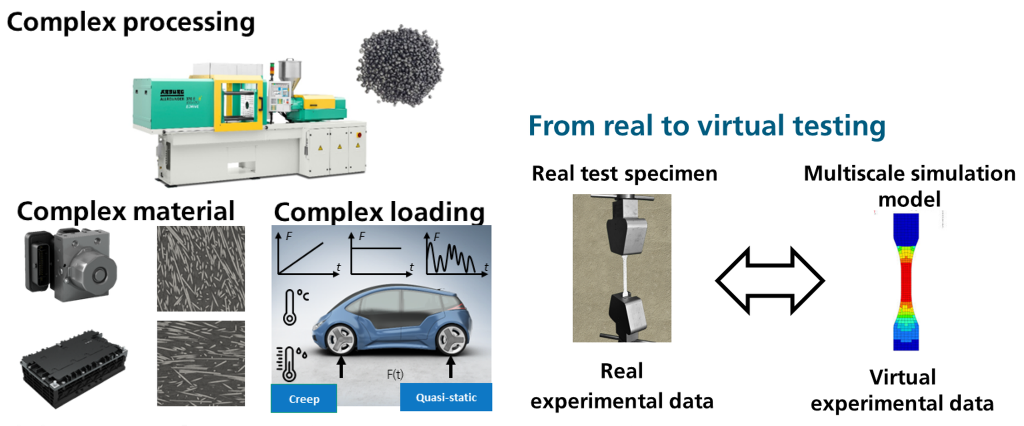
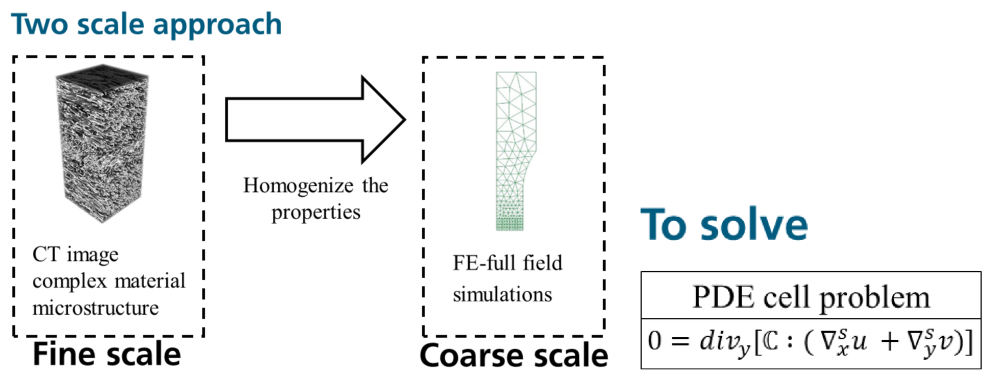
Motivation

Reliability despite complexity

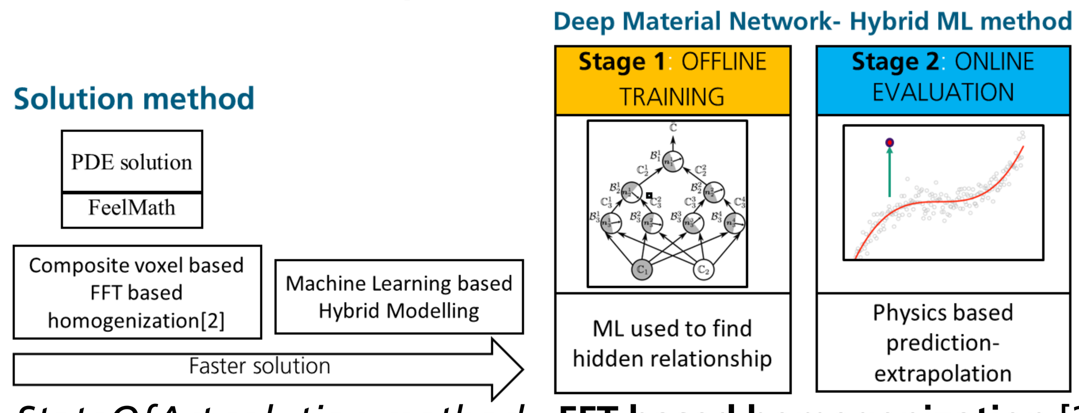


Problem **Real experiments == expensive & sparse.**
Strategy: **Calibrated multiscale simulations ⇒ virtual experimental data.** [1]

Multiscale simulation model and Deep Material Network (DMN)

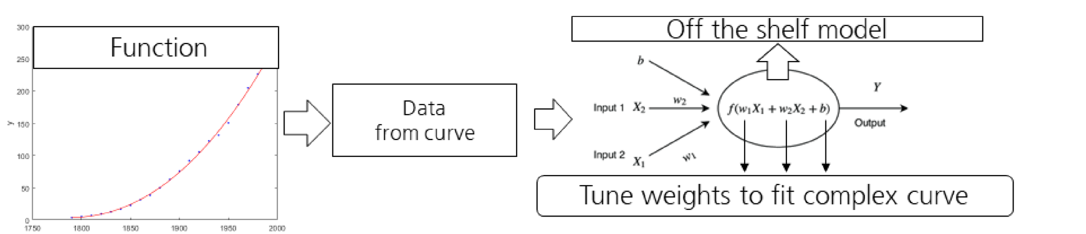


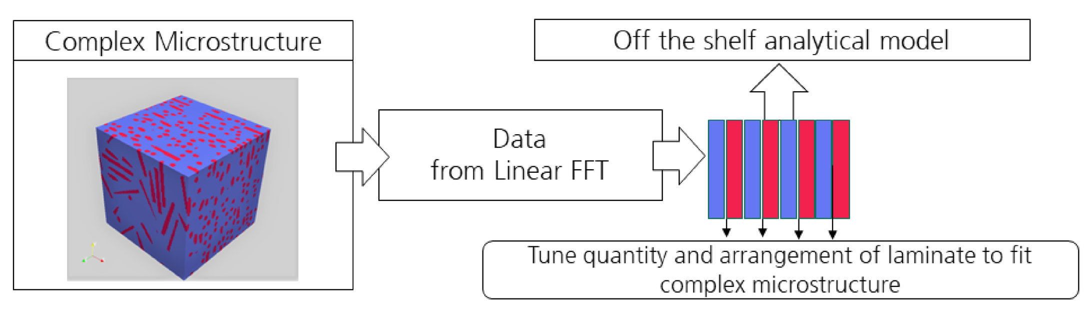
- *Fine scale* : **cell problem ⇔ Homogenization of properties**
- *Coarse scale* : **Global problem**



- *StateOfArt solution method* - **FFT based homogenization** [2]
- *Faster Data driven solution* - **Deep Material Network** [3].

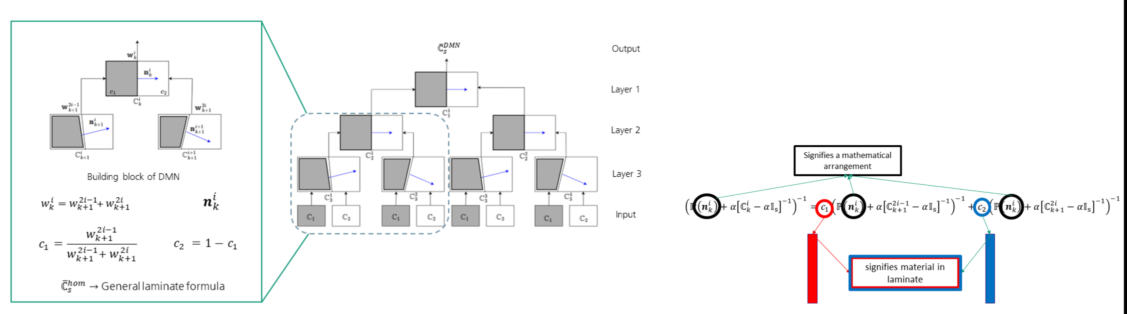
Intuition for DMN





- **Fit Topology like function** [6]

Network Structure

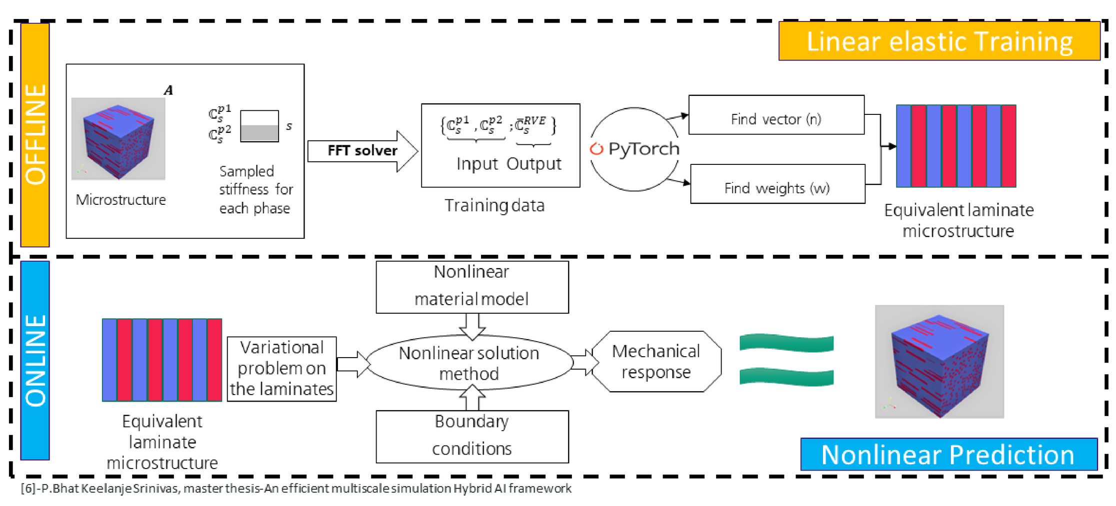


$$J_p(C^{hom}_{act}, C^{hom}_{pred}) = \frac{1}{N_s}\left\| \frac{\|C^{hom}_{act,s} - C^{hom}_{pred,s}\|_{p_{local}}}{\|C^{hom}_{act,s}\|_{p_{local}}} \right\|_{p_{global}} + \lambda \sum_{j=1}^{2}\left(\sum_{i=1}^{2^{k-1}} w^j_{i,BL} - c^j_{hom}\right)^2$$

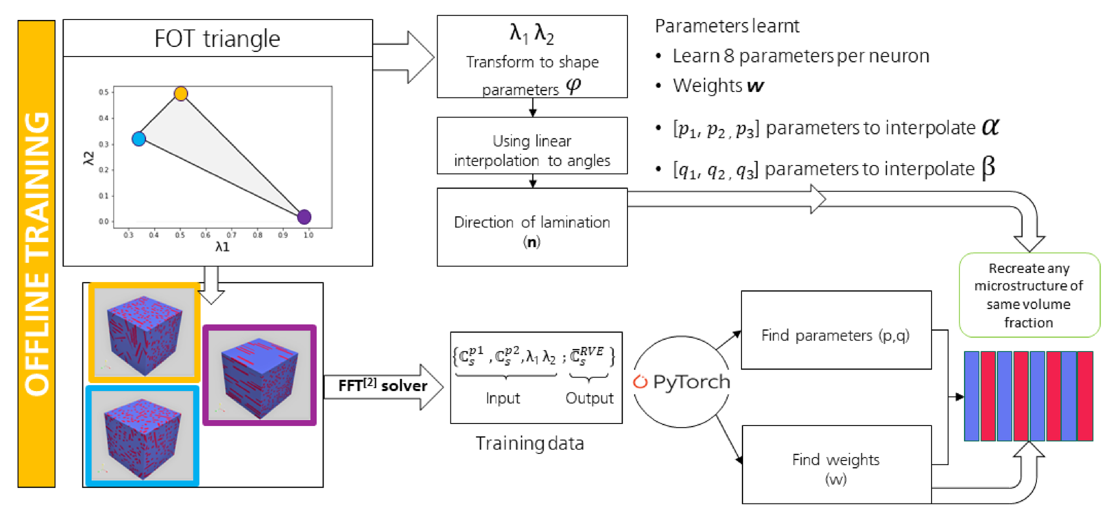
$$p_{local} = 2,\ p_{global} = 1$$

- $J_p \rightarrow \min_{\mathbf{w},\mathbf{n}}$
- *Parameters*: **w** - Weights , **n** - Direction of laminate

Basic workflow and steps



DMN with Fiber Orientation



- **Parametric** network [4].

Numerical setup/ bottlenecks

Error measures

$$e^{plast}_{ij,t} = \frac{\|\sigma^{DMN}_{ij,t} - \sigma^{FFT}_{ij,t}\|}{\|\sigma^{FFT}_{ij,max}\|}$$

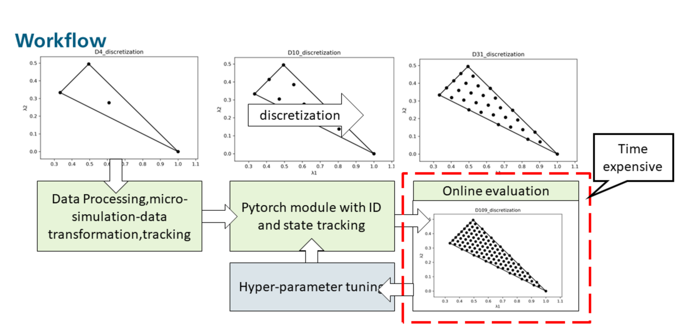
Max and mean Error measures

$$e^{plast}_{max} = \max_{i\in(1,3),j\in(1,3)} \max_{t\in T}\left(e^{plast}_{ij,t}\right)$$

$$e^{plast}_{mean} = \max_{i\in(1,3),j\in(1,3)} mean_{t\in T}\left(e^{plast}_{ij,t}\right)$$

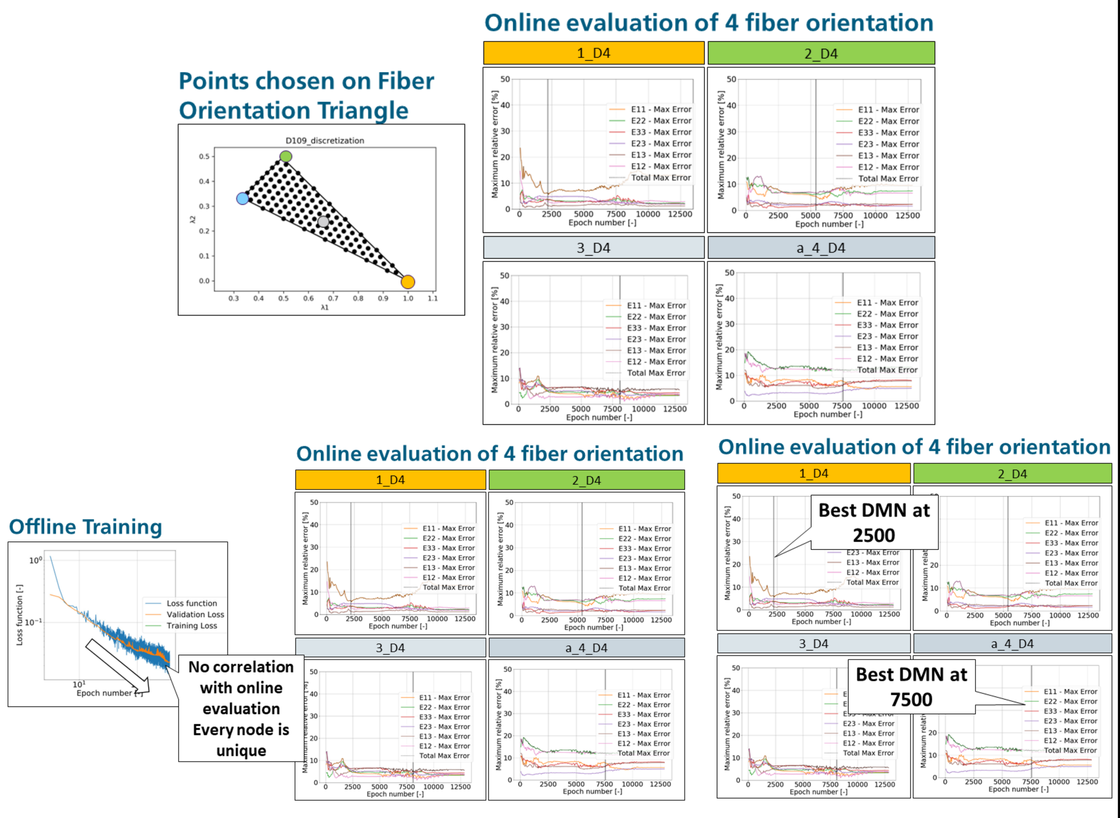
Microstructure parameters

Parameters	Values
Number of voxels	128^3
Fiber diameter	10 µm
Fiber length	100 µm
Length of unit cell	256 µm
Minimum distance between fibers	4 µm
Volume fraction	17.8%

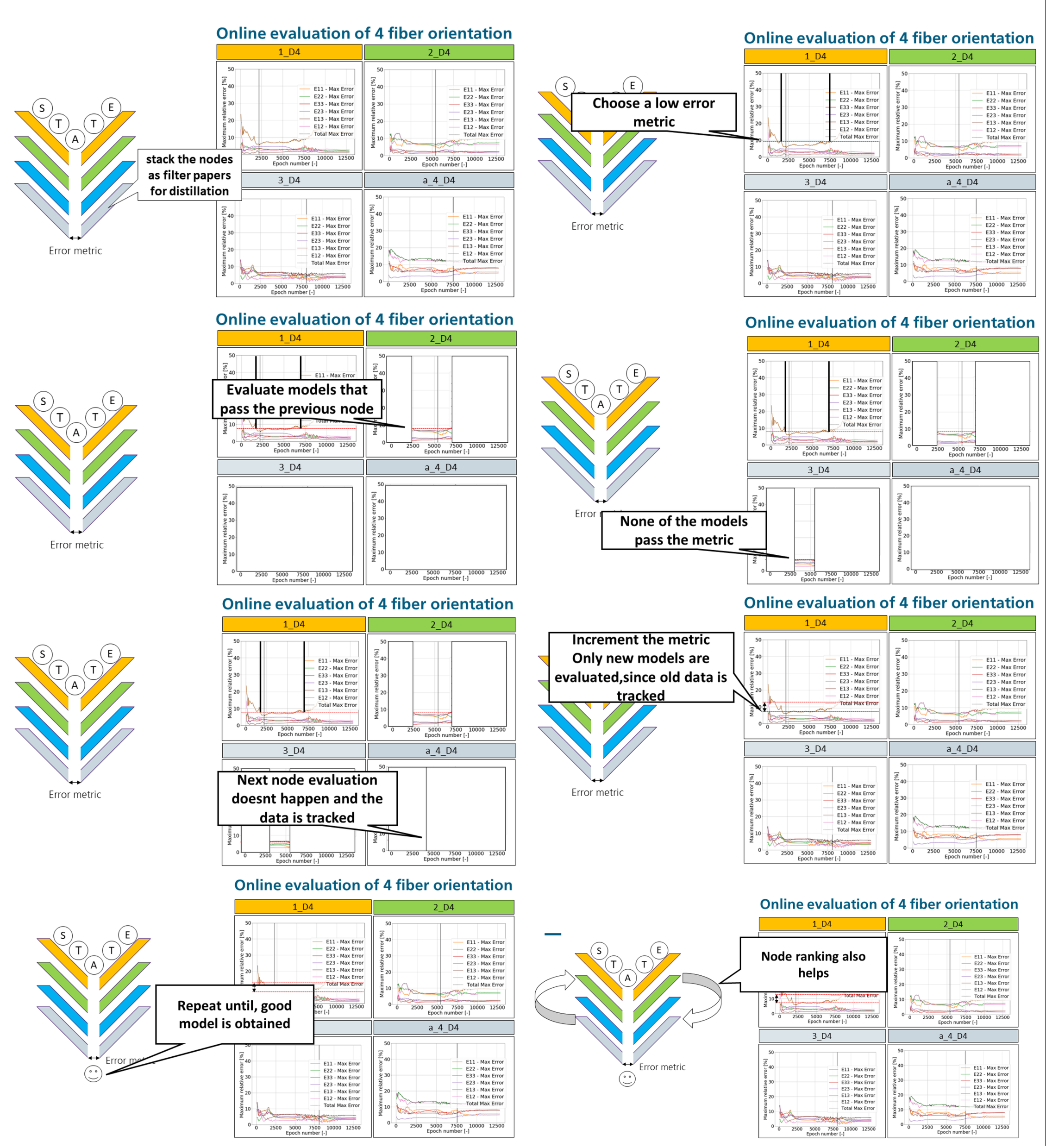


Parameters	Plasticity without distillation
Time for one online evaluation using DMN	60-90 sec
Number of epochs	6000
States storage frequency	Every 50 epochs
Number of states to be evaluated	120
Number of nodes on which evaluation is done	109
Evaluations for orthotropic boundary conditions	6 load cases
Total number of evaluations to validate a DMN training	120x109x6=78480 evaluations
Total time taken for full training evaluation	9-14 days

Model selection challenge



Distillation Algorithm



Parameters	Plasticity-without distillation	Plasticity with distillation
Time for one online evaluation using DMN	60-90 sec	60-90 sec
Number of epochs	6000	6000
States storage frequency	Every 50 epochs	Every 50 epochs
Number of states to be evaluated	120	120
Number of nodes on which evaluation is done	109	109
Evaluations for orthotropic boundary conditions	6 load cases	6 load cases
Total number of evaluations to validate a DMN training	120x109x6=78480 evaluations	800x6=4800 evaluations
Total time taken for full training evaluation	9-14 days	~15 hours

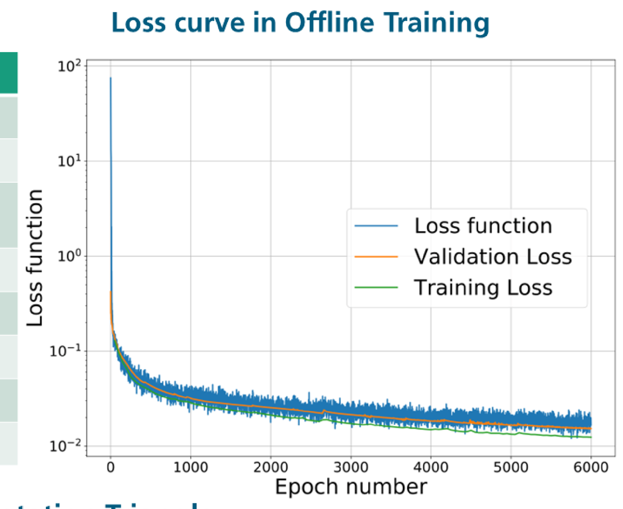
Algorithm takeaways

- **Inspired** by a *physical process* & **novel**.
- **Adaptive** threshold & **robust** algorithm.
- 90 percent reduction in number of evaluations.
- Scope to incorporate *advanced methods*.

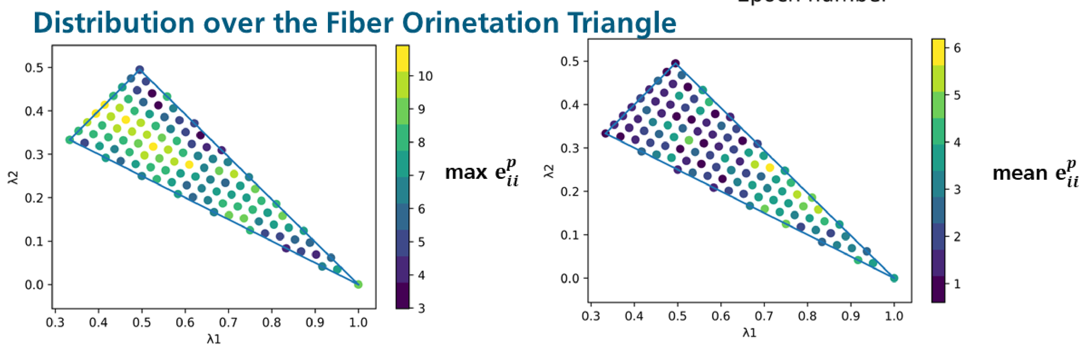
Results

Parameters	Values
Discretization	D31
Training ID	A_0031
Epoch state that passed the distillation	2650
Smallest Loss	0.01108
Mean Validation Error	0.01523
max e^p_{ii}	10.91 %
mean e^p_{ii}	7.31 %
Variance of the distribution	3.1287

Loss curve in Offline Training



Distribution over the Fiber Orinetation Triangle



Process of interest	FFT	DMN	Speed up factor for multiscale simulations
Prediction time for plasticity	30 minutes to 4 hours	<1 minute	>30

Acknowledgement

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References

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