

KI-basierte Materialmodellierung für Holzwerkstoff

AI based Constitutive Modeling for Wood

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Motivation

Continuum Damage Mechanics

Veneer / Single Ply

Neural Network Architecture and Training

Results

Ply Wood / Laminate [0, 90, 90, 0]

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Aims & Scope

- elasto-damage response of anisotropic materials
 - highly direction dependent
 - multiple, interacting damage mechanisms
 - classical damage modeling strategies
 - closed-form constitutive laws
 - phenomenological (thus limited)
 - suitable for FEM implementation
 - homogenization
 - model of the resolved micro structure (RVE)
 - non-linear constitutive law cannot be deduced directly
 - FE^2 — extremely computer resource hungry
- **machine learning surrogate model**
- train an ANN to learn the complex constitutive law
implement into FEM

Continuum Damage Mechanics

plane stress; Voigt notation with $\gamma_{xy} = 2\varepsilon_{xy}$

$$\boldsymbol{\sigma} = (\sigma_{xx} \ \sigma_{yy} \ \sigma_{xy})^T, \quad \boldsymbol{\varepsilon} = (\varepsilon_{xx} \ \varepsilon_{yy} \ \gamma_{xy})^T$$

Hooke's law

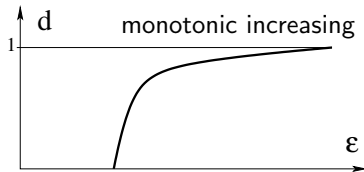
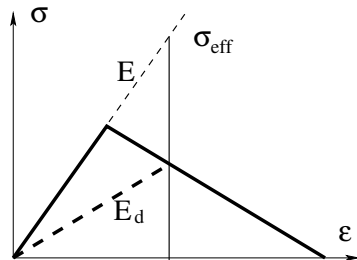
$$\boldsymbol{\sigma} = \mathbf{E}\boldsymbol{\varepsilon}$$

elasticity tensor

$$\mathbf{E} = \begin{pmatrix} E_{11} & E_{12} & 0 \\ E_{21} & E_{22} & 0 \\ 0 & 0 & E_{33} \end{pmatrix}$$

elasto-damage response

$$\boldsymbol{\sigma} = \mathbf{E}_d \boldsymbol{\varepsilon}, \quad \text{with} \quad \mathbf{E}_d = f(\mathbf{E}, d)$$



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Hashin Damage Model



damaged elasticity tensor, as implemented in ABAQUS

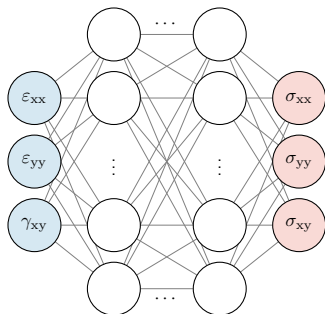
$$\mathbf{E}_d^{(\text{Hashin})} = f(\mathbf{E}, d_f^t, d_f^c, d_m^t, d_m^c, d_s)$$

damage initiation and evolution based on the failure modes

- fiber rupture in tension
- fiber buckling and kinking in compression
- matrix cracking under transverse tension and shearing
- matrix crushing under transverse compression and shearing

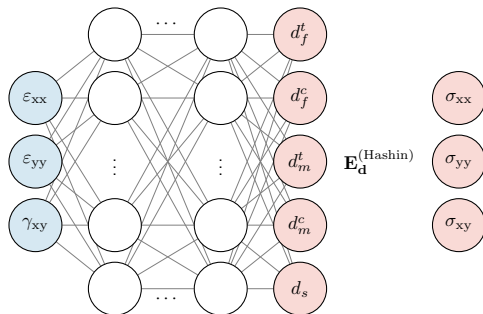
Neural Network Architecture (Single Ply)

network size: 4 layers with 64 neurons, ReLU activation function



$$f_{\theta}^{\sigma} : \mathbb{R}^3 \mapsto \mathbb{R}^3, \quad \varepsilon \mapsto \sigma = f_{\theta}^{\sigma}(\varepsilon)$$

stress mapping



$$f_{\theta}^d : \mathbb{R}^3 \mapsto \mathbb{R}^5, \quad \varepsilon \mapsto \mathbf{d} = f_{\theta}^d(\varepsilon)$$

damage variable mapping

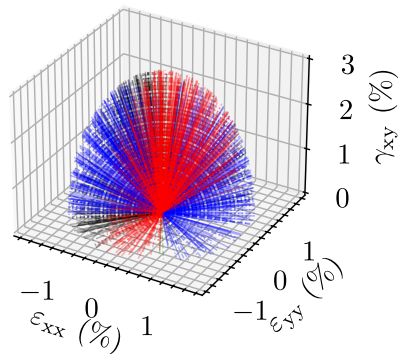
Neural Network Training

data base generation — FEM single element
1600 radial strain paths with 400 increments each
1200 used for training and 400 for validation

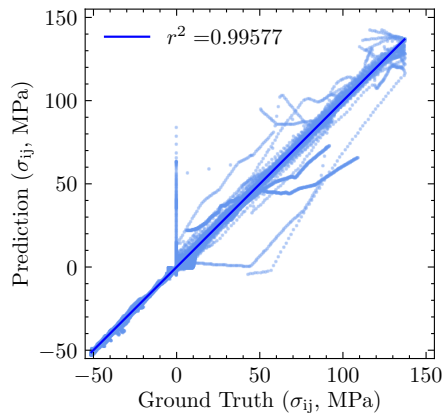
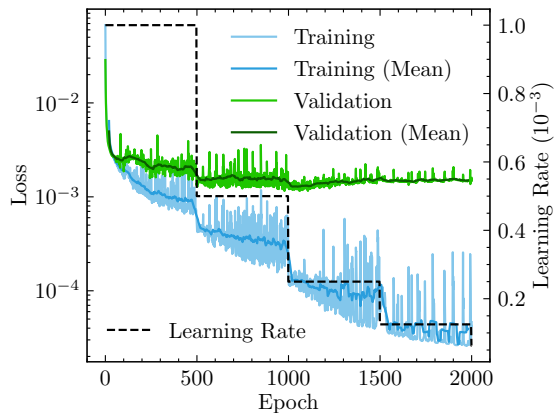
$$\arg \min_{\theta} \sum_{n=1}^N \sum_{m=1}^M \mathcal{L} \left(f_{\theta} (\epsilon_{n,m}), \hat{d}_{n,m} \right)$$

- N ... number of loading paths
 M ... number of increments per path
 $\mathcal{L}(\cdot, \cdot)$... loss function
 f_{θ} ... neural network output
 $\epsilon_{n,m}$... input strain
 $\hat{d}_{n,m}$... Hashin damage variables
 θ ... neural network parameters

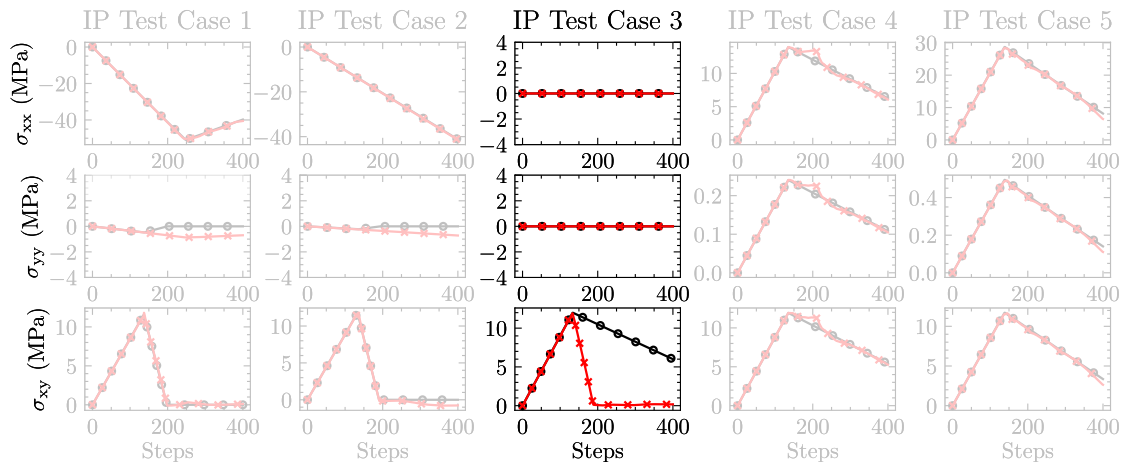
- no damage
- both damaged
- only fiber damaged
- only matrix damaged



Neural Network Training

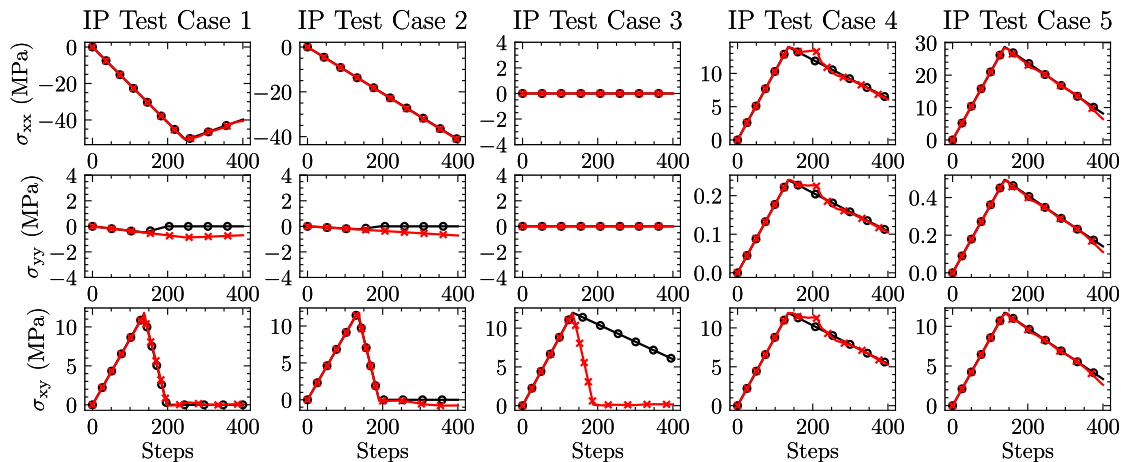


Comparison around Simple Shear: Stresses



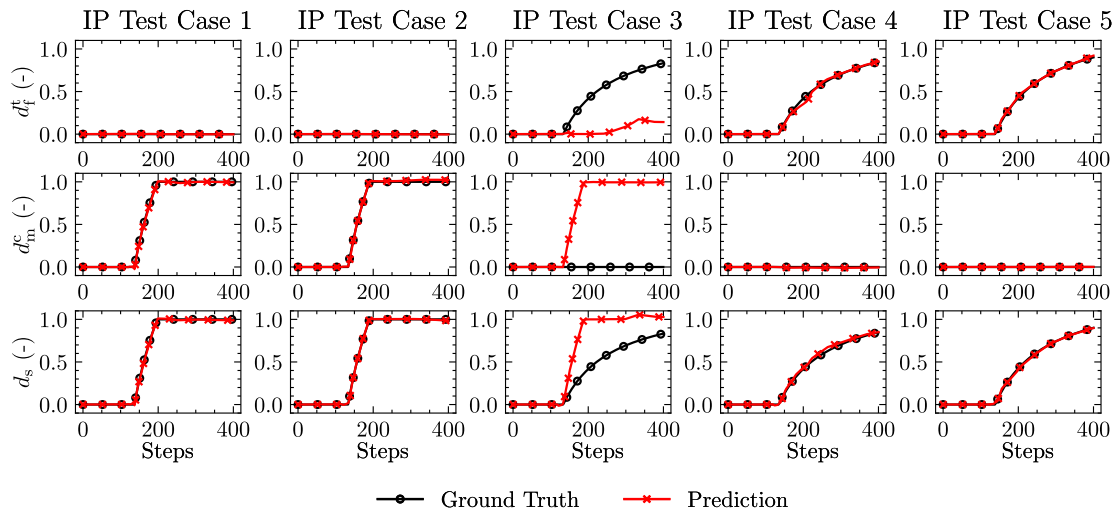
—●— Ground Truth —×— Prediction

Comparison around Simple Shear: Stresses



—●— Ground Truth —×— Prediction

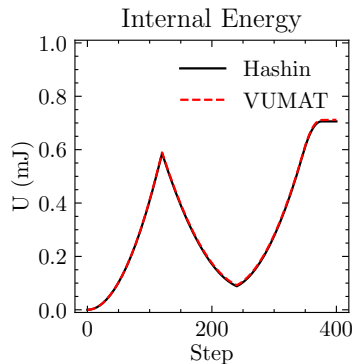
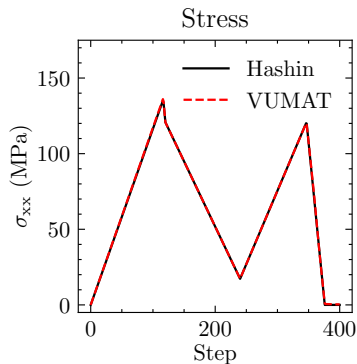
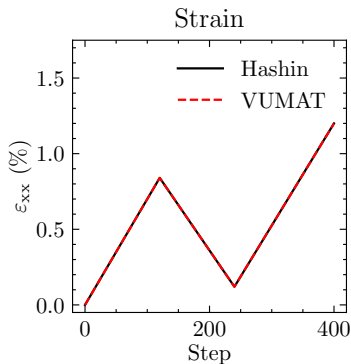
Comparison: Damage Variables



FEM Implementation — VUMAT

enforce damage mechanics principles — monotonic rising damage variables

loading–unloading–reloading sequence



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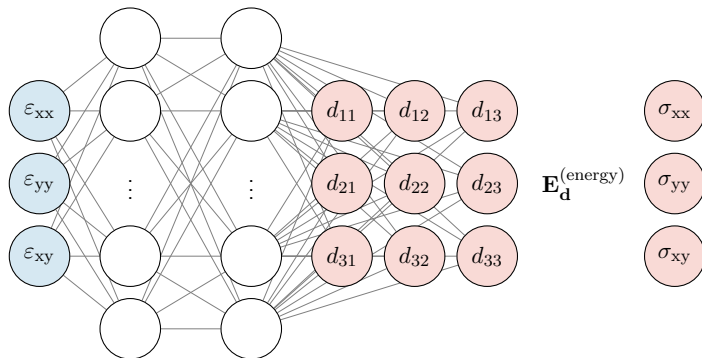
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Network Architecture for Ply Wood

network size: 4 layers with 64 neurons, ReLU activation function



$$f_{\theta}^D : \mathbb{R}^3 \rightarrow \mathbb{R}^{3 \times 3} \quad \varepsilon \mapsto \mathbf{D} = f_{\theta}^D(\varepsilon); \quad \mathbf{E}_d^{(\text{energy})} = (\mathbf{I} - \mathbf{D}) \mathbf{E} (\mathbf{I} - \mathbf{D})^T$$

Neural Network Training

data base generation for the (homogenized) ply wood response — as before
training on the stresses

damage variables not known explicitly; but deduced by the ANN

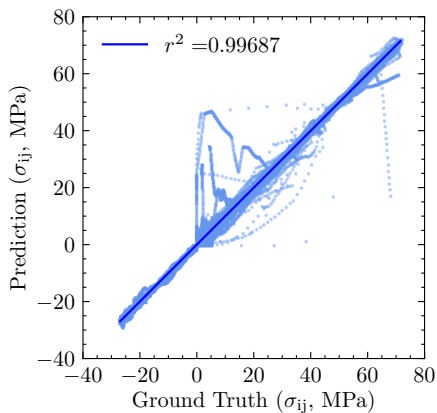
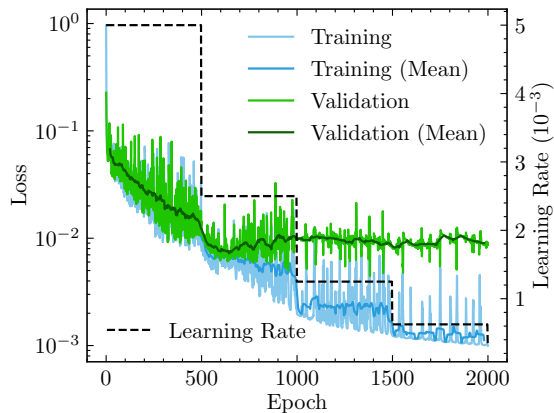
$$\arg \min_{\theta} \sum_{n=1}^N \sum_{m=1}^M \mathcal{L}(\sigma_{n,m}, \hat{\sigma}_{n,m})$$

with

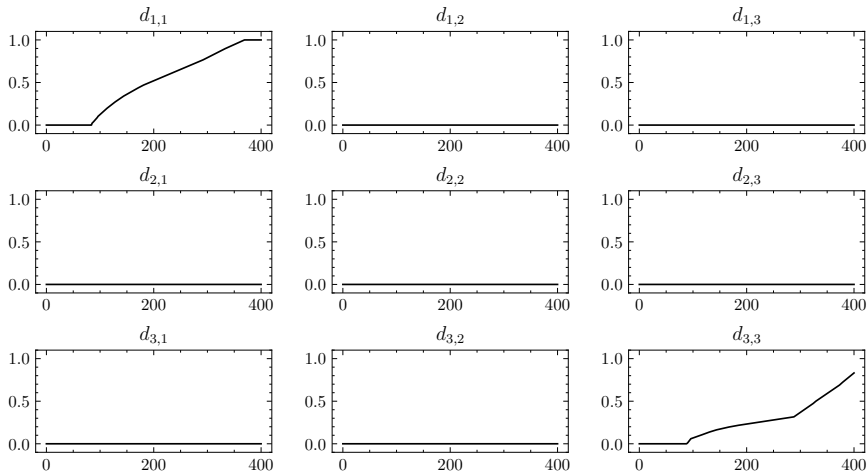
$$\sigma_{n,m} = (\mathbf{I} - \mathbf{D}) \mathbf{E} (\mathbf{I} - \mathbf{D})^T \epsilon_{n,m}$$

$$\sigma_{n,m} = (\mathbf{I} - f_{\theta}^D(\epsilon_{n,m})) \mathbf{E} (\mathbf{I} - f_{\theta}^D(\epsilon_{n,m}))^T \epsilon_{n,m}$$

Neural Network Training

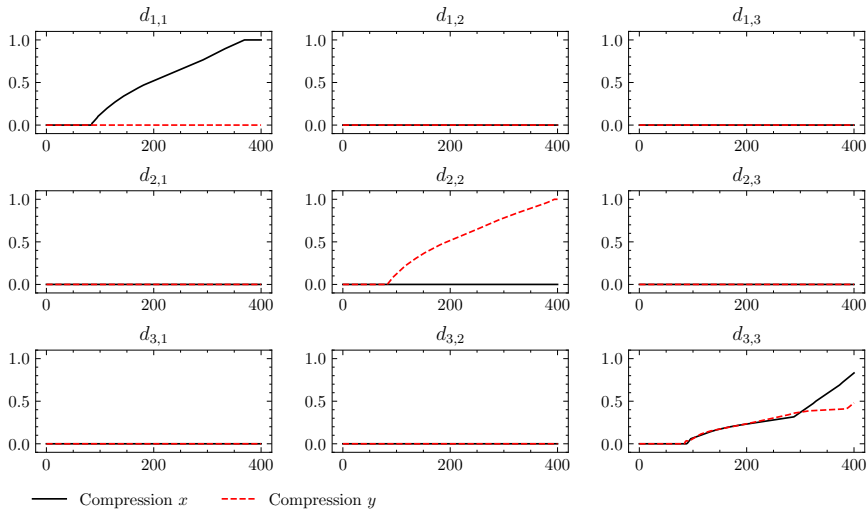


Damage Tensor for Various Test Cases

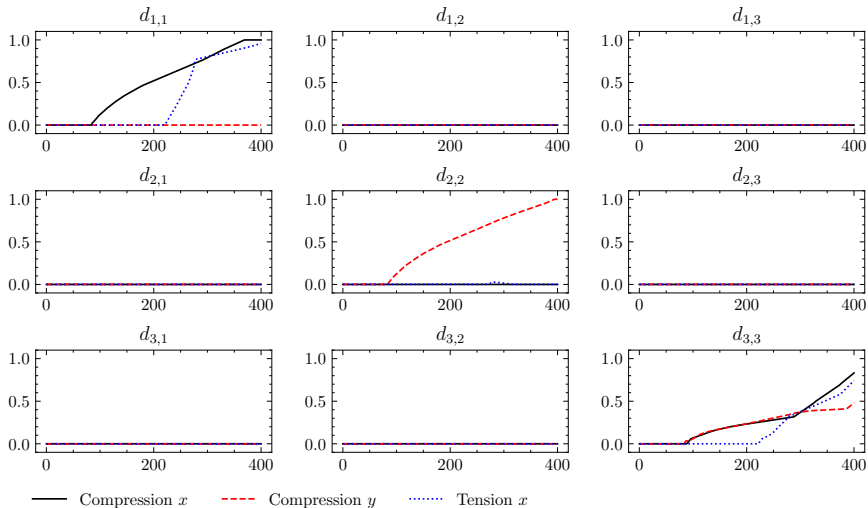


— Compression x

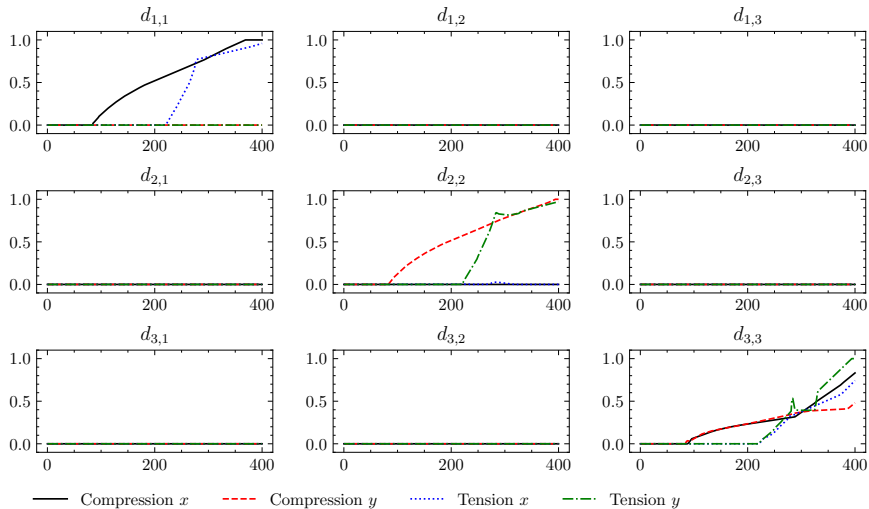
Damage Tensor for Various Test Cases



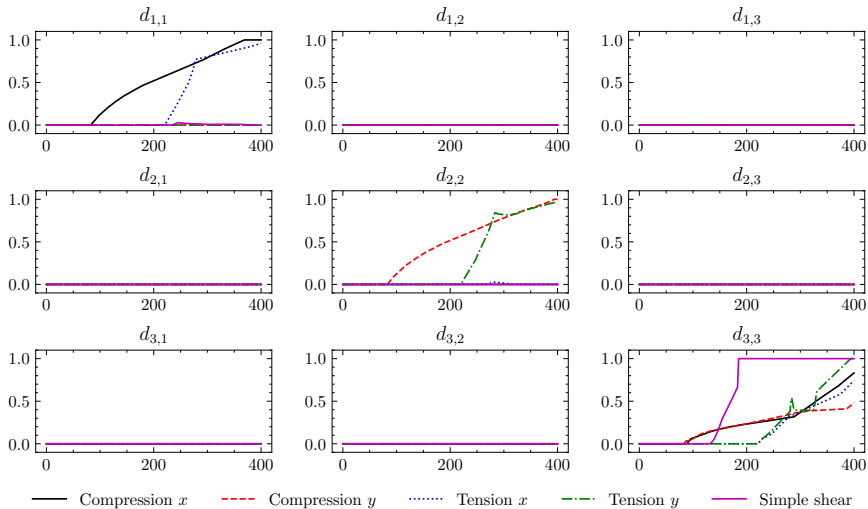
Damage Tensor for Various Test Cases



Damage Tensor for Various Test Cases



Damage Tensor for Various Test Cases



Discussion of the Damage Tensor



- 4th order damage tensor is formulated
evolution is deduced
for which there is no explicit expression
- diagonal damage tensor
because of 0/90 layup
expected to be non-symmetric for general cases

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- machine learning / AI methods to predict the elasto-damage response of anisotropic materials as wood, ply wood, and composites
- reproduce an existing continuum damage model for a single ply / veneer
- implement the ANN as constitutive law into FEM
- apply damage mechanics principles to capture unloading and reloading
- predict homogenized ply wood response for which there is no closed form
- extract the evolution of the implicit damage tensor

work in progress

- further verification on ply wood
- investigate response to non-radial strain loading
- application to structural analyses with non-uniform mesh size

Hashin Damaged Elasticity Tensor

$$\mathbf{E}_d^{(\text{Hashin})} = \frac{1}{\Delta} \begin{pmatrix} (1 - d_f)E_x & (1 - d_f)(1 - d_m)\nu_{yx}E_x & 0 \\ (1 - d_f)(1 - d_m)\nu_{xy}E_y & (1 - d_m)E_y & 0 \\ 0 & 0 & (1 - d_s)G_{xy}\Delta \end{pmatrix}$$

with $\Delta = 1 - (1 - d_f)(1 - d_m)\nu_{xy}\nu_{yx}$.