a place of mind

Characterization and Calibration of Progressive Damage Models for Composites: Experimental, Virtual and Machine Learning Methods

ICCM-23
Belfast, Northern Ireland
30th July – 4th August, 2023

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Acknowledgements

Faculty colleagues

- ❑ Prof. Anoush Poursartip
- ❑ Prof. Göran Fernlund

Present and former students/staff of the UBC Composites Group/CRN

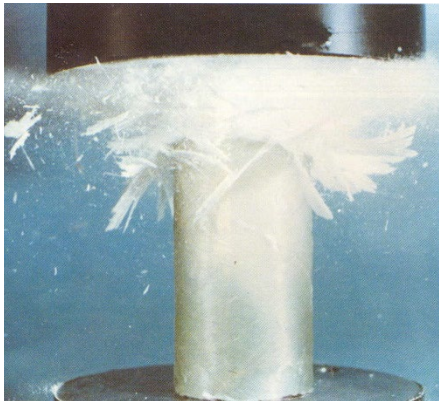
- ❑ Dr. Alireza Forghani
- ❑ Dr. Mina Shahbazi
- ❑ Dr. Ofir Shor
- ❑ Ms. Carla McGregor
- ❑ Mr. Scott McClennan
- ❑ Dr. Anthony Floyd
- ❑ Dr. Kevin Williams
- ❑ Dr. Isabelle Paris
- ❑ Ms. Ingrid Kongshavn

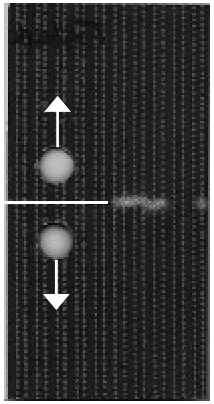
Collaborators / Sponsors

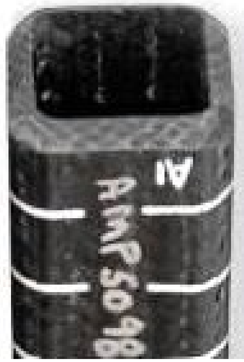
- ❑ Natural Sciences and Engineering Research Council (NSERC) - Canada
- ❑ University of Bristol
- ❑ Livermore Software Technology Corp (LSTC)
- ❑ Boeing
- ❑ DLR (German Aerospace Centre)
- ❑ General Motors Corporation
- ❑ CMH-17 Crashworthiness Working Group
- ❑ Ford Research & Advanced Engineering
- ❑ Politecnico di Torino

Motivation

- Interested in simulating damage progression and energy absorption in *large-scale* composite structures up to failure
- Development and implementation of efficient computational fracture/damage modelling methodologies within commercial FE software packages that can be readily used by industry
- Applications of interest:
  - damage-tolerant design of composite structures
  - penetrating and non-penetrating impact events
  - in-plane fracture of notched specimens
  - energy absorption in crash events







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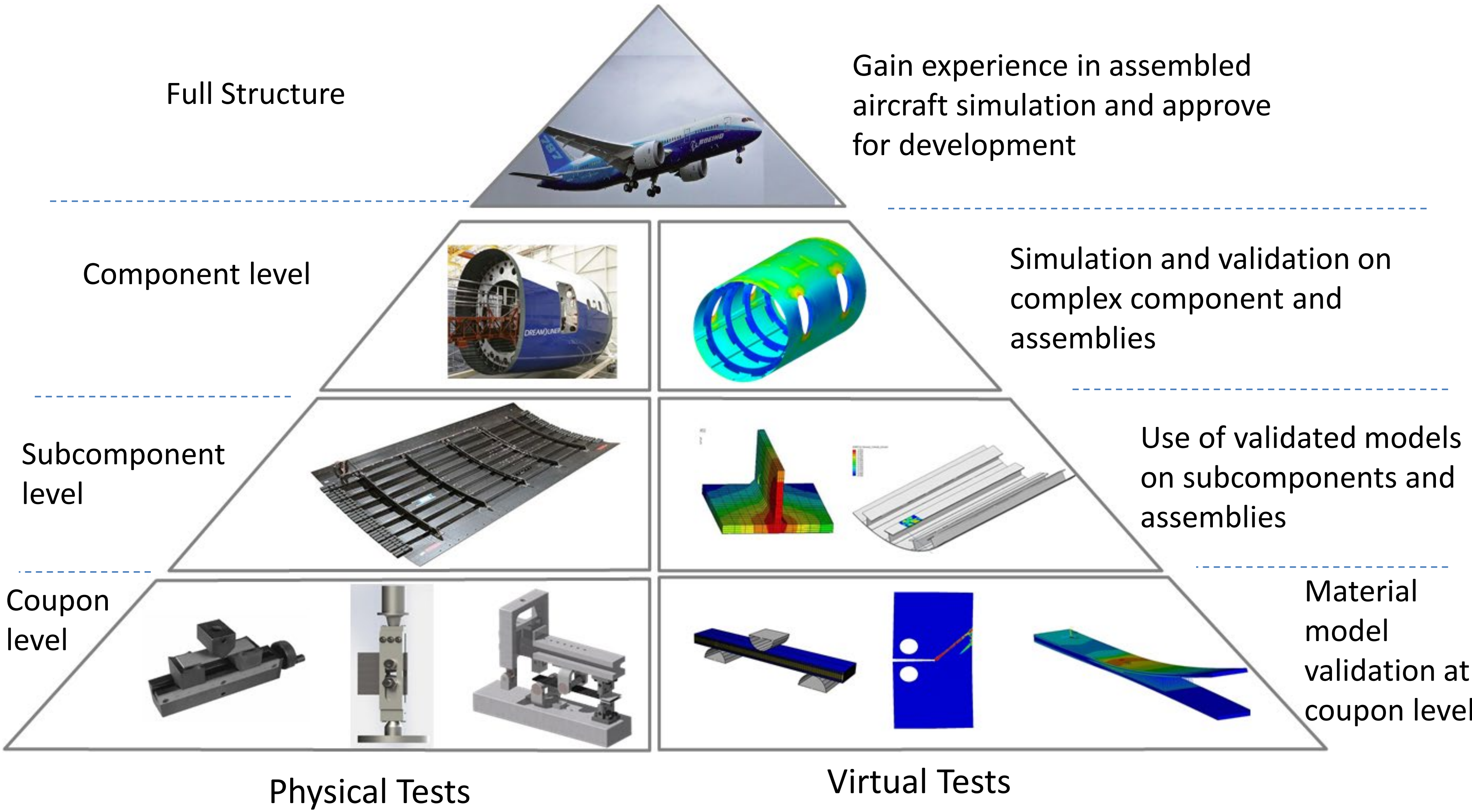
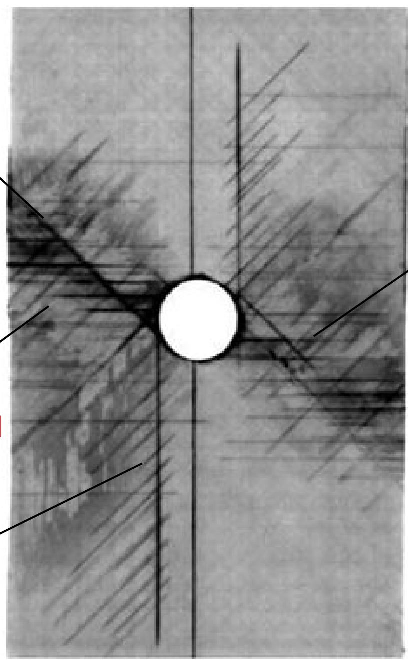
Building-Block Pyramid

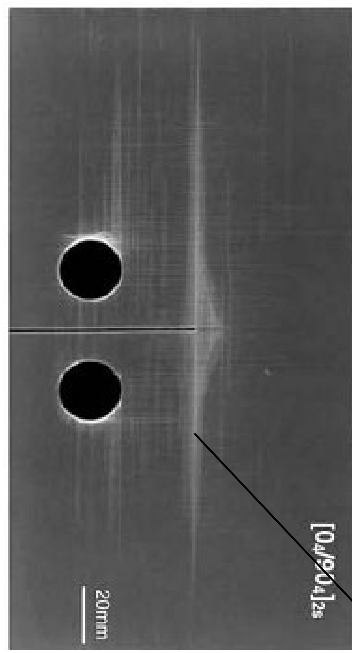


Damage Mechanisms

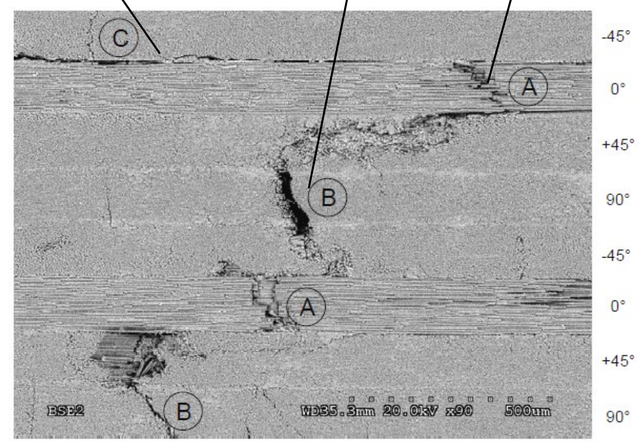
- Damage mechanisms and structural failure in composites are complex and depend on layup, loading scenario and geometry
- This complexity is a result of interplay between intra-laminar and inter-laminar damage modes



Open hole tensile test (OHT)



Over-height compact tension test (OCT)



Through-thickness view of a quasi-isotropic OCT specimen

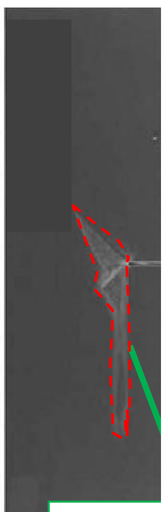
- Hallett, S.R. and Wisnom M.R., 2006. *Journal of Composite Materials,* 40(14), pp. 1229-1245.
- Li X, Hallett SR, Wisnom MR, Zobeiry N, Vaziri R, Poursartip A.. Composites Part A: Applied Science and Manufacturing. 2009;40(12):1891-9.

Smeared Fracture Zone vs. Localized Macroscopic Cracks

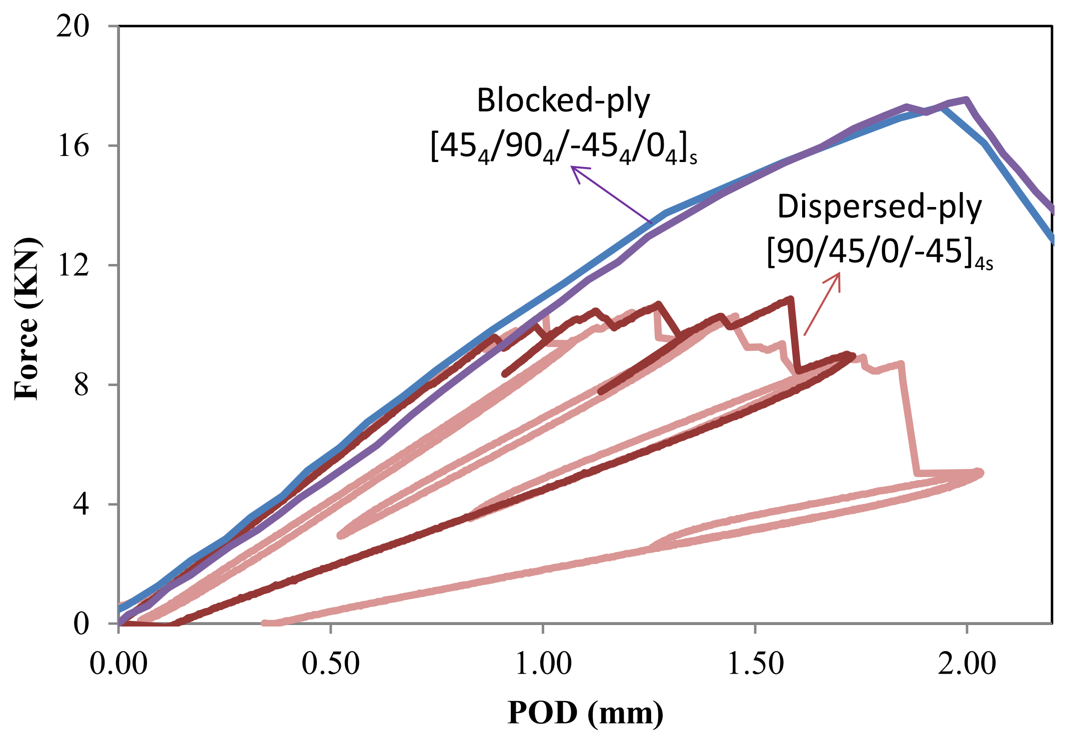
- Form and extent of damage mechanisms are strongly influenced by laminate layup

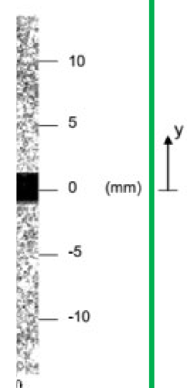
Blocked-ply quasi-isotropic
IM7/8552 CF
[45_4/90_4/

Dispersed-ply quasi-isotropic
ate



Extensiv
zone bou
cracks ar

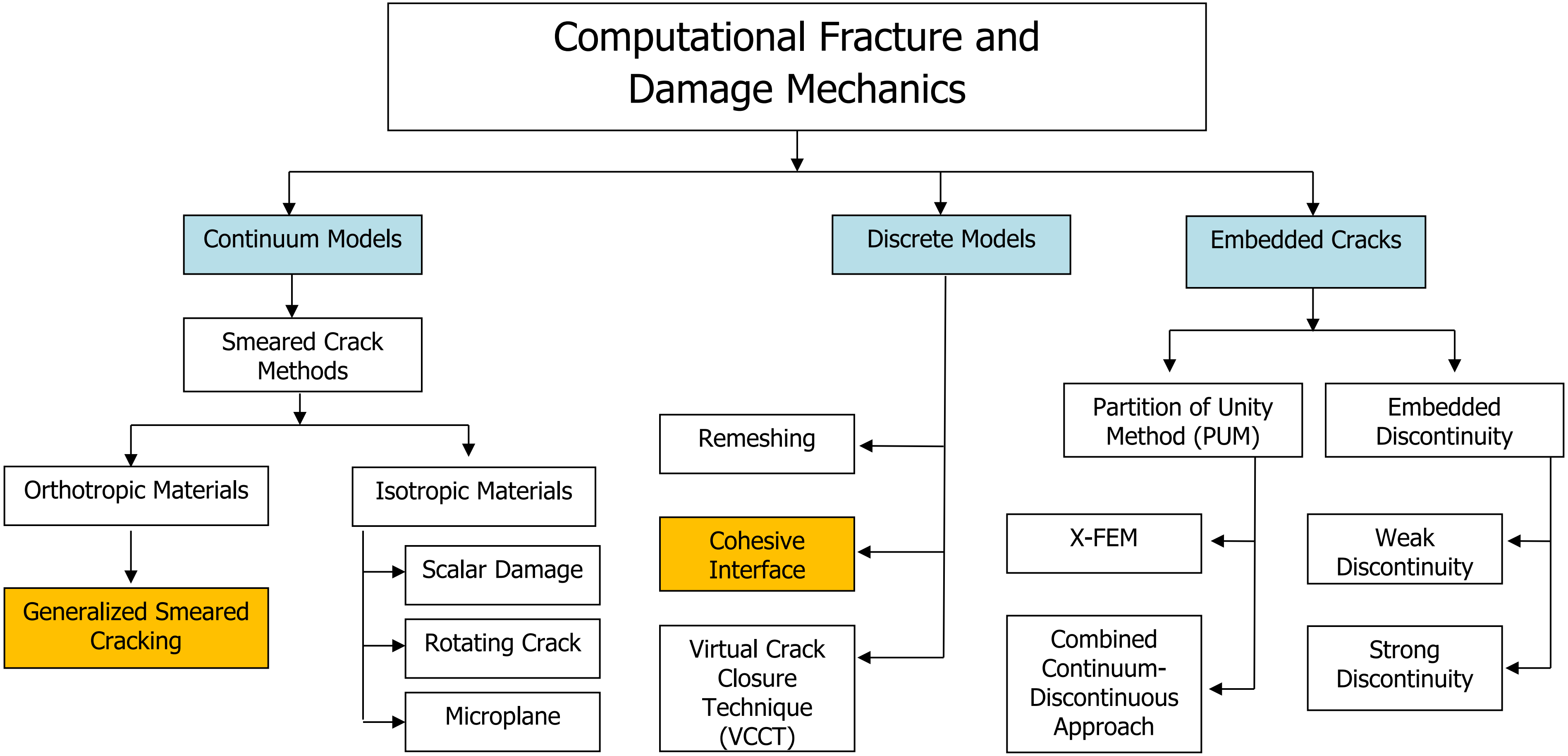




akage
with minor delamination

- Zobeiry, N., Vaziri, R., Poursartip, A. 2015. Compos. Part A-Appl. S., 68(0): 29-41.
- Li, X., Hallett, S.R., Wisnom, M.R., Zobeiry, N., Vaziri, R., Poursartip, A. 2009. Compos. Part A-Appl. S., 40(12): 1891-1899.

Taxonomy of Computational Fracture and Damage Mechanics



- A. Forghani, M. Shahbazi, N. Zobeiry, A. Poursartip and R. Vaziri, Chapter 6, *Numerical Modelling of Failure in Advanced Composite Materials*, Camanho, P.P. and Hallett, S. (Eds.), Woodhead Pub Ltd, 2015.
- J. Reiner, R. Vaziri , *Structural Analysis of Composites with Finite Element Codes*, Beaumont, P.W.R. and Zweben, C.H. (Eds.), Comprehensive Composite Materials II, Vol 8, pp. 61-84. Oxford: Academic Press, 2018

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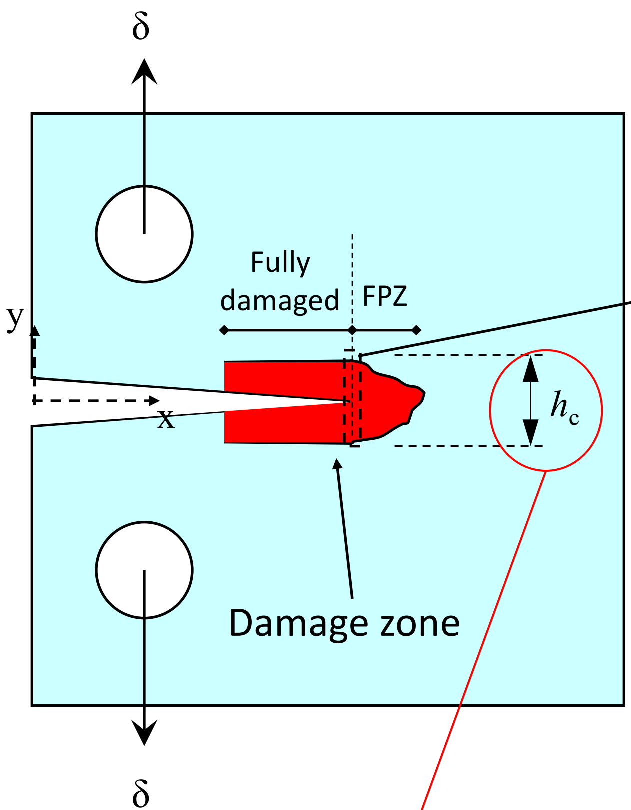
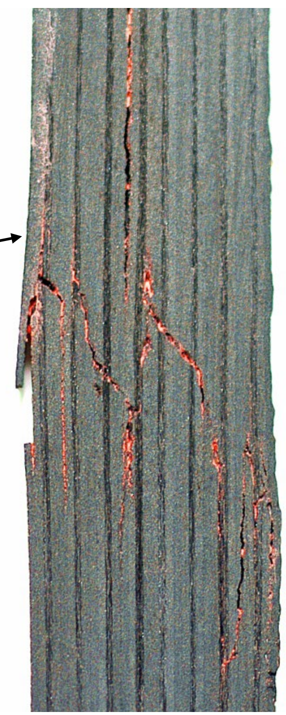
Focus of this talk

- Dispersed laminate layups are widely used in construction of practical composite structures
- For this class of problems, the nonlinear structural response up to failure as well as the bulk of energy absorption in impact/crash loading applications is dominated by fibre fracture
- Reliable simulations of such events depends on accurate representation of the progressive fracture behaviour of the laminate
- For efficient progressive damage and failure (PDF) analysis of large-scale structures, the laminate is typically represented using a single shell element through the thickness
- Several material models are available in commercial FE codes (e.g. LS-DYNA, Abaqus/Explicit) for PDF simulations and many benchmark studies have been undertaken (e.g. CMH-17 Crashworthiness Working Group) to evaluate their performance
- Successful simulations are based on material models with parameters that are calibrated using experiments that elicit the physics of the fracture process at the laminate level

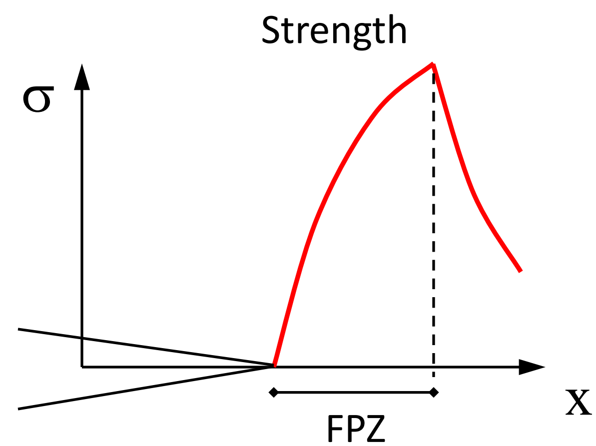
Strain-Softening Response

Unlike truly brittle materials, in *quasi-brittle materials* such as composites, size of the fracture process zone (FPZ) cannot be neglected compared to the size of the structure.





Damage zone
(through-thickness)

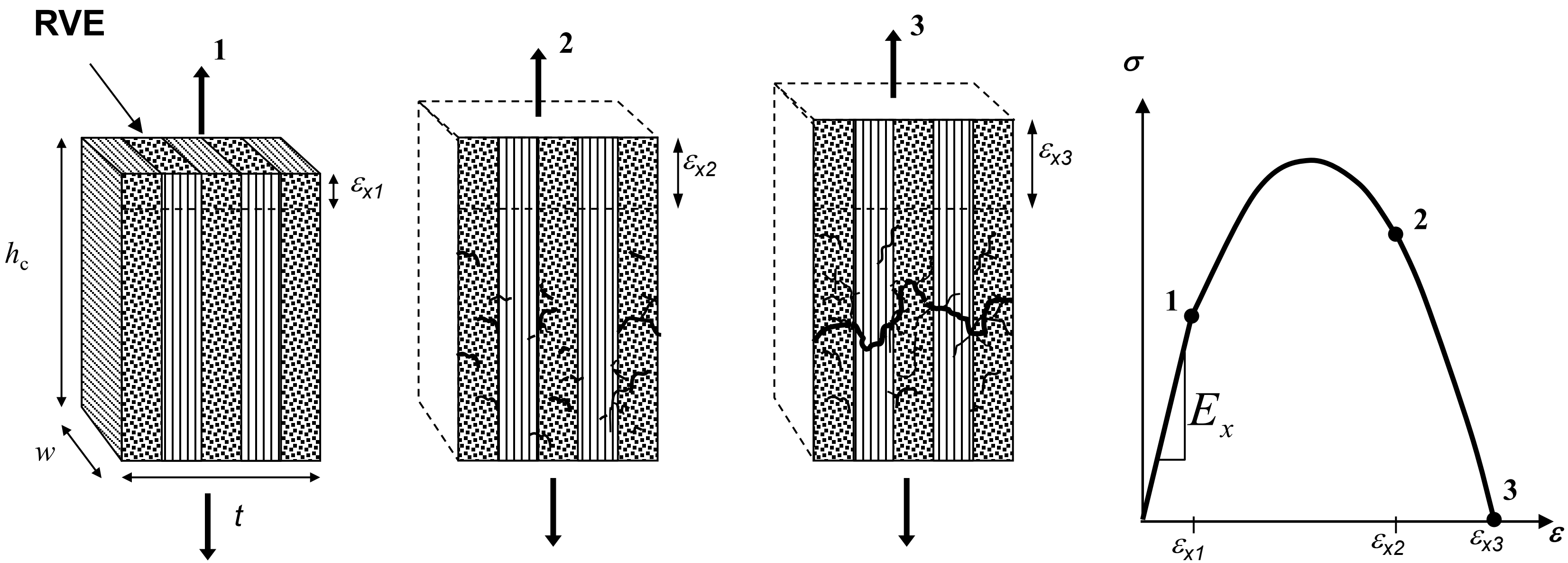


Softening behaviour in FPZ

h_c = material characteristic length (height)

Intra-laminar Damage: Continuum Approach

- UBC Composite Damage Model (CODAM)
- First introduced by Williams *et al** (1998)
- Overall behaviour of sub-laminate is considered
- Damage is smeared over the repeating unit volume (sub-laminate)



Elastic (undamaged)

Matrix cracks, delamination and some fibre breakage

Complete failure

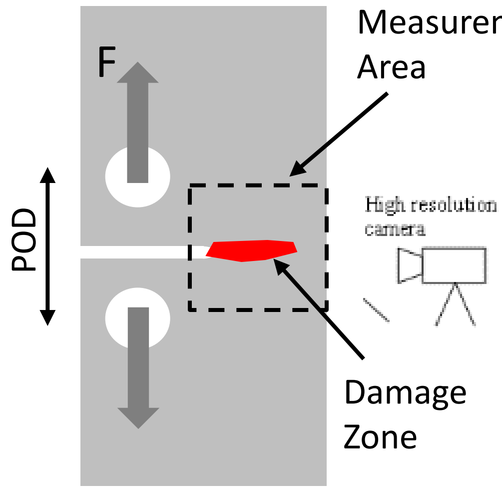
strain-softening model

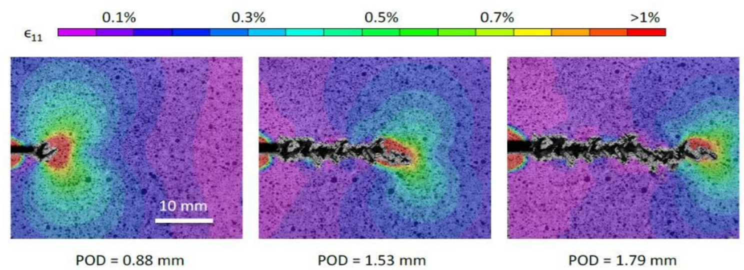
*K. Williams, *Ph.D. Thesis*, The University of British Columbia (1998)
K. Williams, R. Vaziri, and A. Poursartip, *Int. J. Solids & Struct.*, **40**, 2267-2300 (2003)

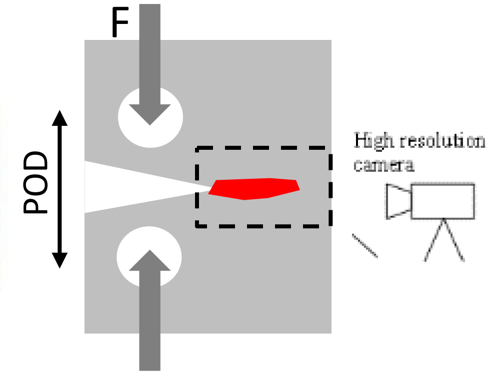
Progressive Damage – Physical Testing

Over-height Compact Tension (OCT) Test

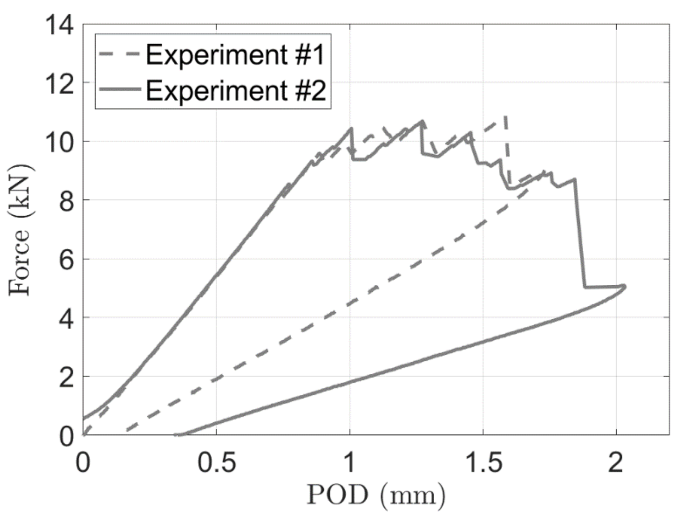
Compact Compression (CC) Test

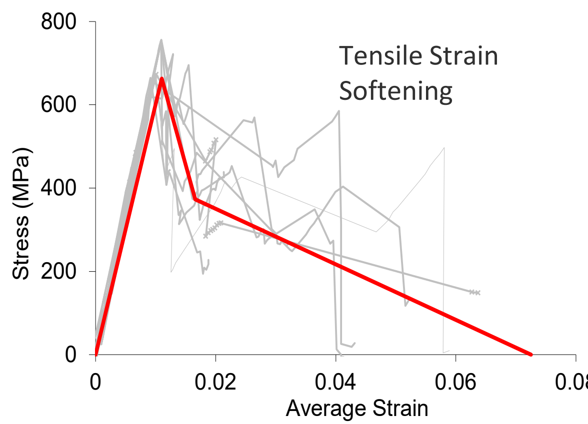


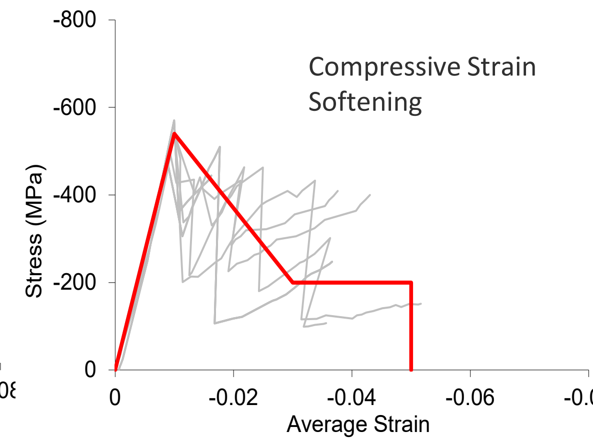




$[90/45/0/-45]_{4s}$ IM7/8552 CFRP



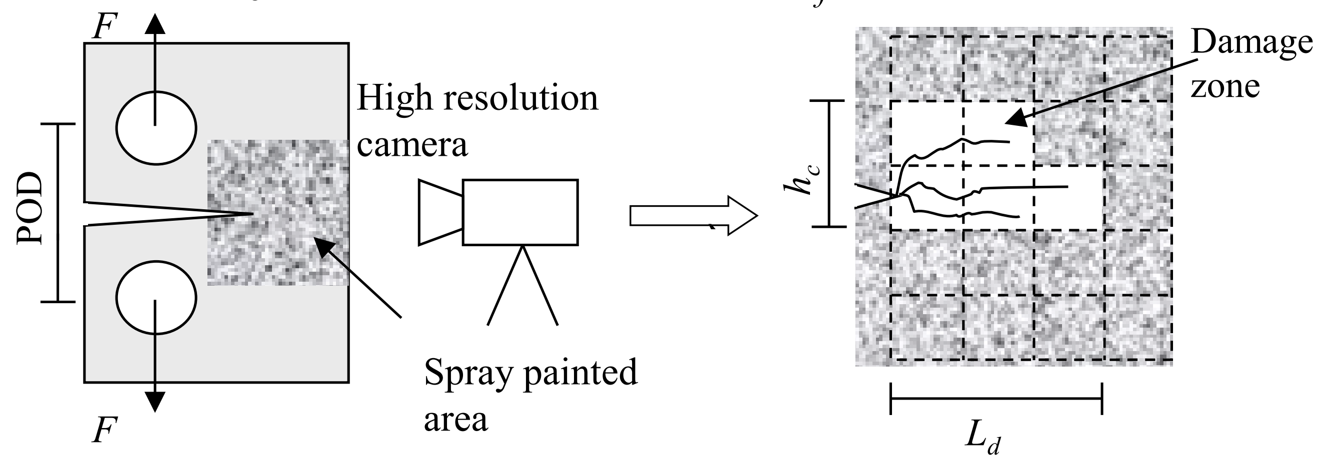




N. Zobeiry, R. Vaziri and A. Poursartip, 'Characterization of Strain-Softening Behaviour and Failure Mechanisms of Composites under Tension and Compression', *Composites Part A*, Vol. **68**, 29-41, (2015)

Calibration of CODAM2 – Nonlocal (MAT219 in LS-DYNA)

Notched coupon tests (OCT, CC) combined with the *DIC technique*, and inverse FE analysis are used to obtain damage initiation strain, ε^{i}, damage height, h_c, and fracture energy, G_f .



Parameters extracted from tests

ε^{i}

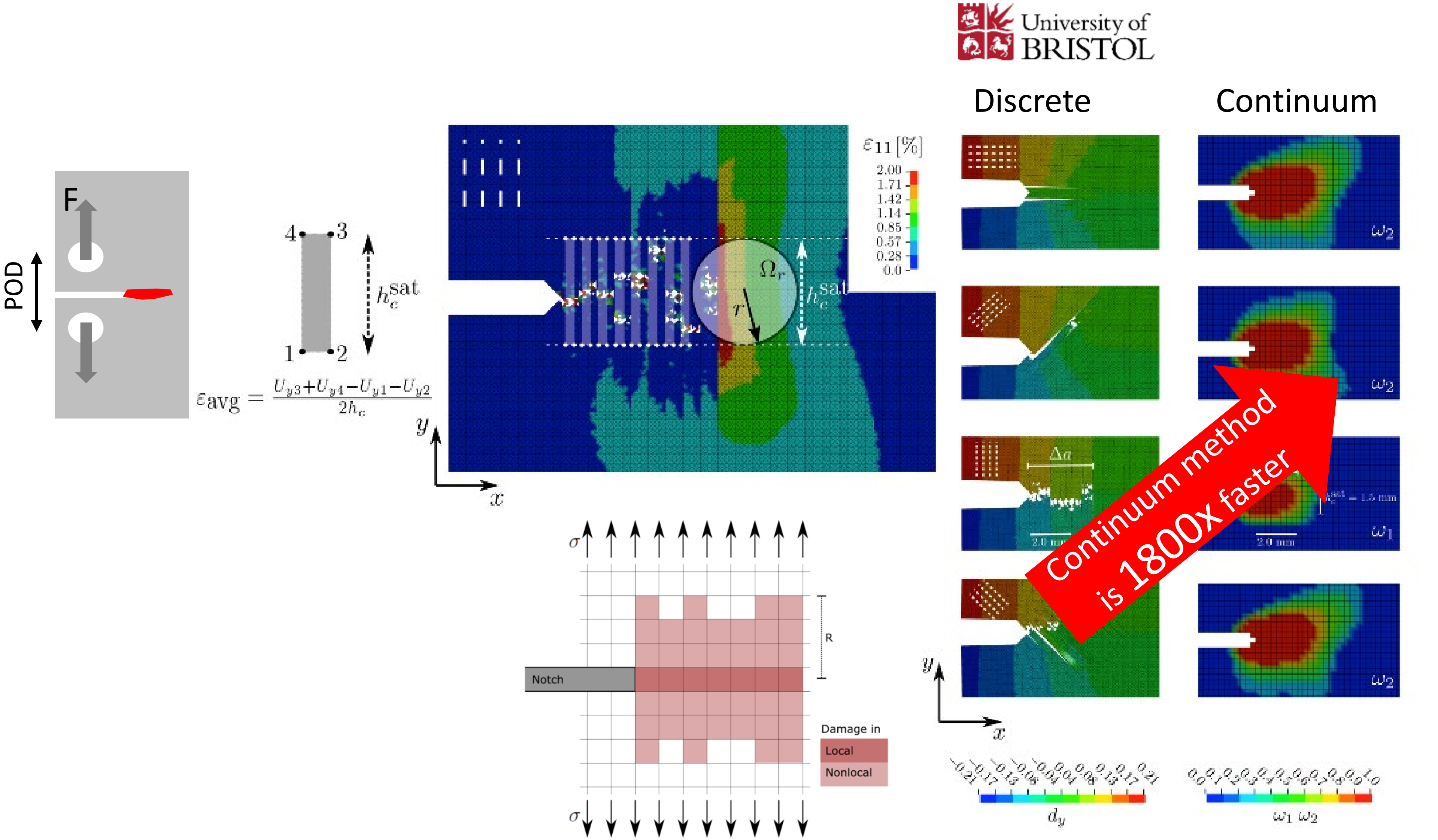
h_c

$\left.\begin{matrix} L_d \\ F-POD \end{matrix}\right\} \rightarrow G_f$

$\varepsilon^{i}_{m}, \varepsilon^{i}_{f}$	Damage Initiation Strains	
r_1, r_2	Non-local Averaging Radii	***CODAM2 Model Parameters***
$\varepsilon^{s}_{m}, \varepsilon^{s}_{f}$	Damage Saturation Strains	

N. Zobeiry, A. Forghani, C. McGregor, S. McClennan, R. Vaziri and A. Poursartip, 'Effective Calibration and Validation of a Nonlocal Continuum Damage Model for Laminated Composites,' *Composite Structures*, Vol. **173**, pp. 188-195, (2017)

Calibration of CODAM2 - Assisted by High Fidelity FEA

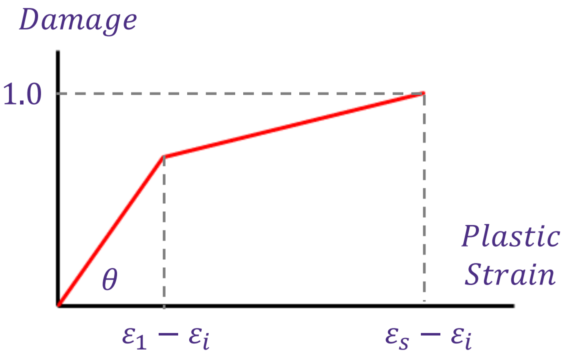


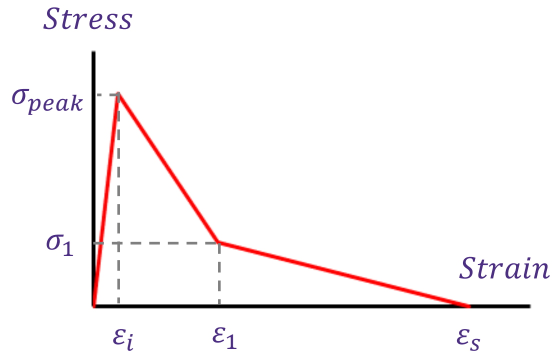
J. Reiner, X. Xu, N. Zobeiry, R. Vaziri, SR Hallett and MR. Wisnom (2021), *Virtual characterization of nonlocal continuum damage model parameters using a high fidelity finite element model,* Composite Structures, Volume 256, 113073.

Calibration of Strain-Softening Curves for LS-DYNA MAT81 (coupled plasticity-damage model)

List of Parameters to Calibrate

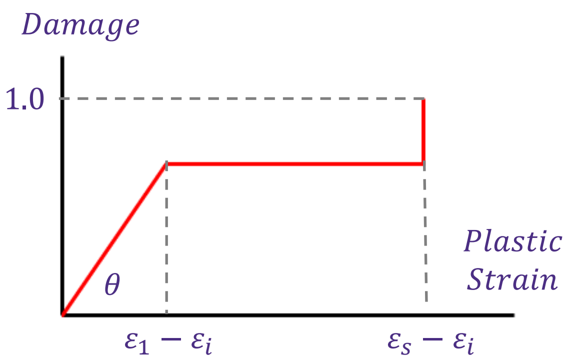
Tension

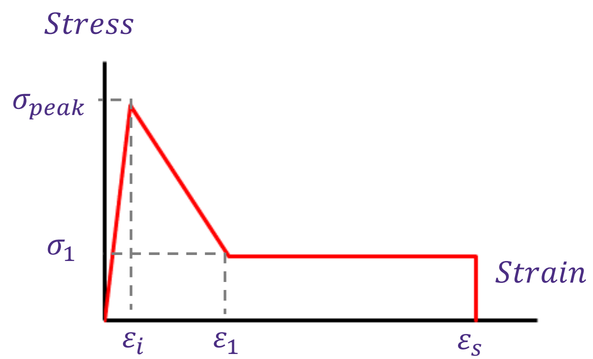




$E, G_f, \sigma_{peak}, \theta, \sigma_1$

Compression

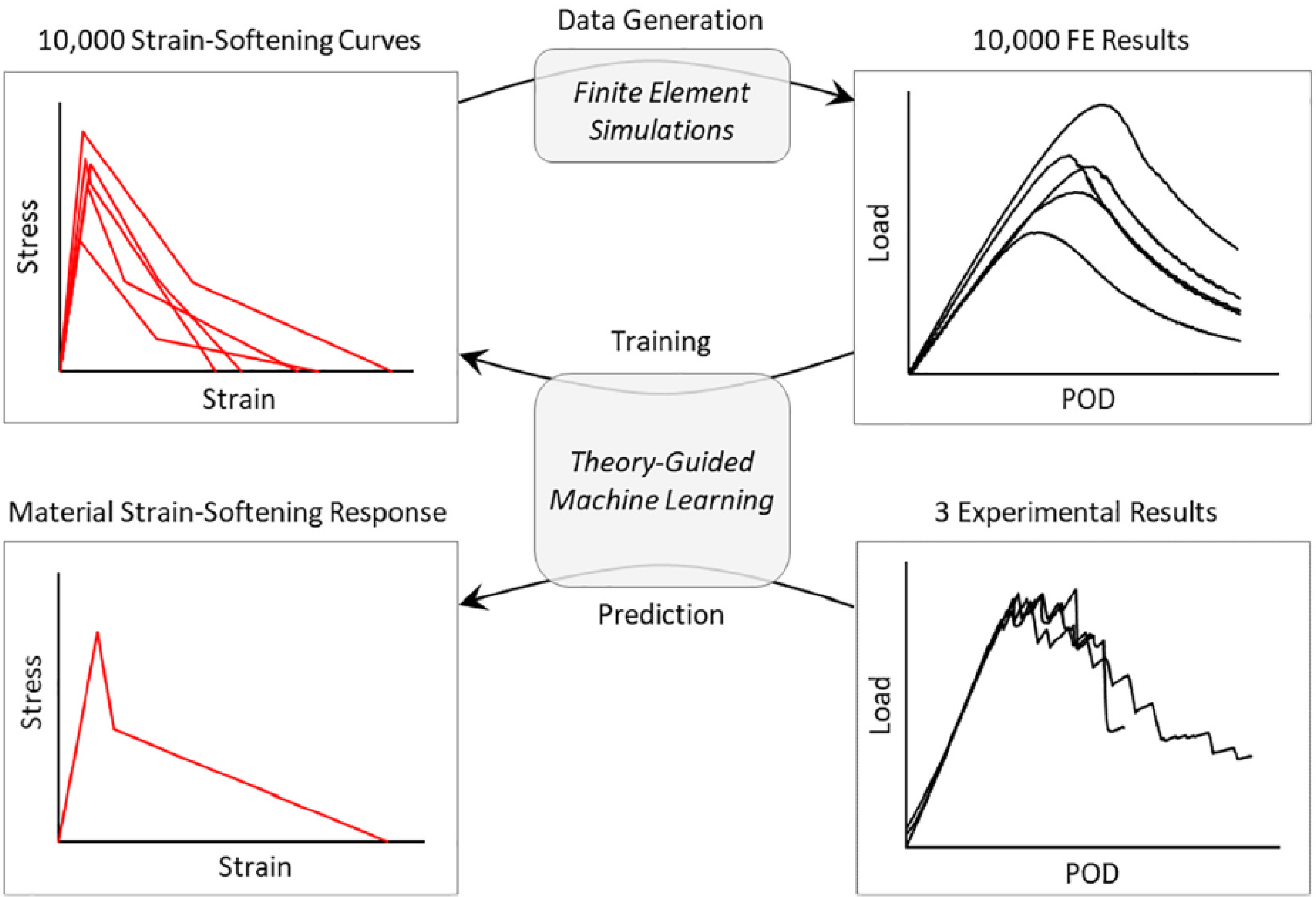




$E, G_f, \sigma_{peak}, \theta, \sigma_1$

Calibration – Assisted by Machine Learning

- 4 neural networks (NN) in series (each NN has 4 hidden layers and 10 nodes per layer)
- High-level API in Python (version 3.6.8), Tensorflow (version 1.8.0)
- FE: 1 simulation in 5 minutes
- ML: 10,000 simulations in 5 minutes



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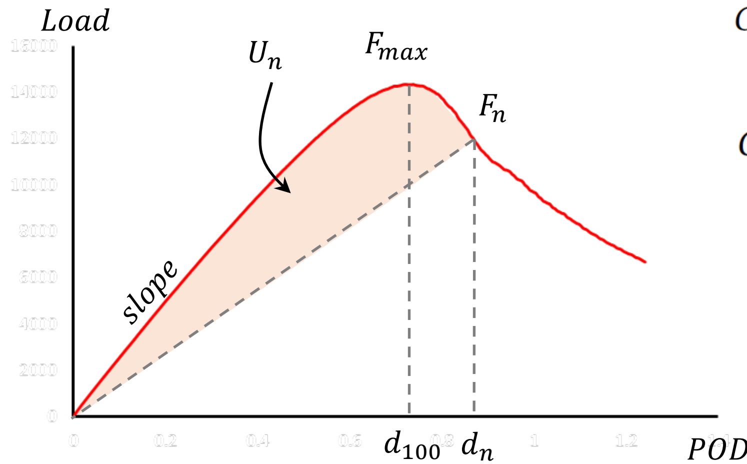
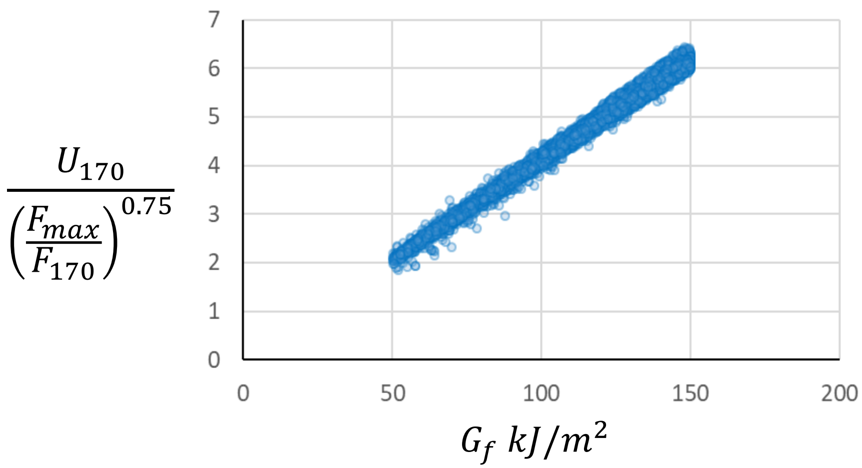
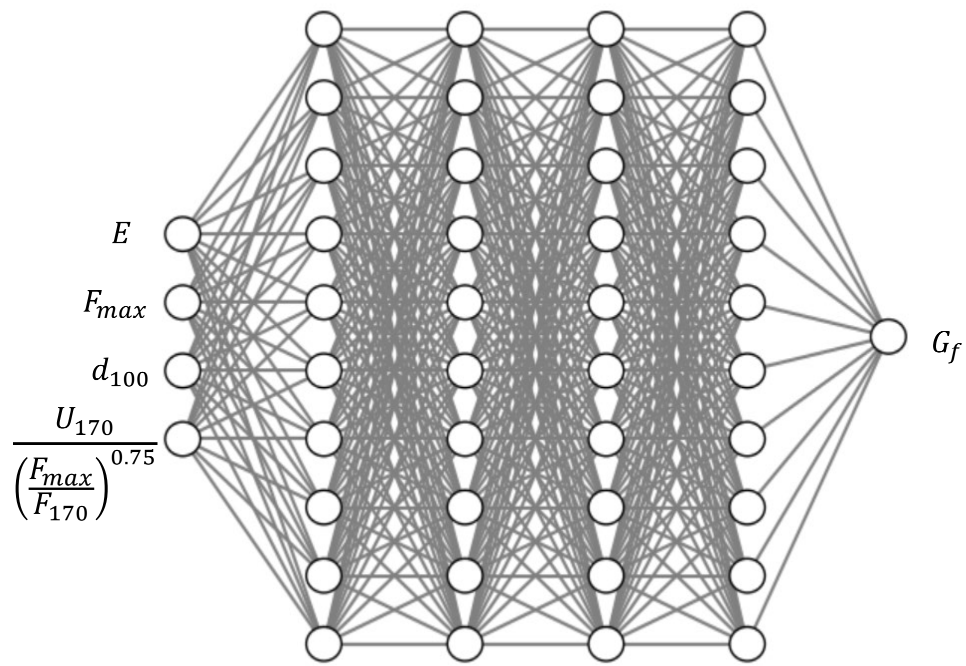
Theory Guided Machine Learning (TGML)



$$G_f \propto \frac{\Delta U}{Crack\ \ Length} \propto \frac{\Delta U}{f\,(Loss\ \ of\ \ Stifness)} \propto \frac{\Delta U}{f\,(\frac{F_1}{d_1}, \frac{F_2}{d_2})}$$

$$G_f \propto \frac{U_{170}}{\left(\frac{F_{max}\,/\,d_{100}}{F_{170}\,/\,d_{170}}\right)^{0.75}} \propto \frac{U_{170}}{\left(\frac{F_{max}}{F_{170}}\right)^{0.75}}$$





N. Zobeiry, J. Reiner, R. Vaziri (2020), *Theory-guided machine learning for damage characterization of composites,* Composite Structures, Volume 246, 112407.

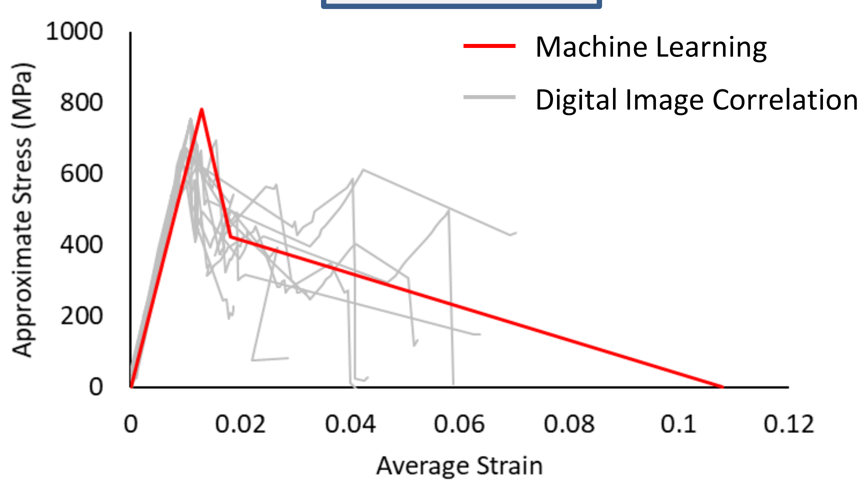
Tensile Failure Characterization

$E, \frac{U_{170}}{\left(\frac{F_{max}}{F_{170}}\right)^{0.75}}, d_{100}, F_{max}$ → Neural Network 1 → G_f

$E,\ G_f, d_{100}, F_{max}, U_{80}, U_{90}$ → Neural Network 2 → σ_{peak}

$E, G_f, \sigma_{peak}, d_{100}, F_{max}$
F_{110}, F_{120} → Neural Network 3 → θ

$E, G_f, \sigma_{peak}, \theta, d_{100}, F_{max}$
F_{110}, F_{120} → Neural Network 4 → σ_1



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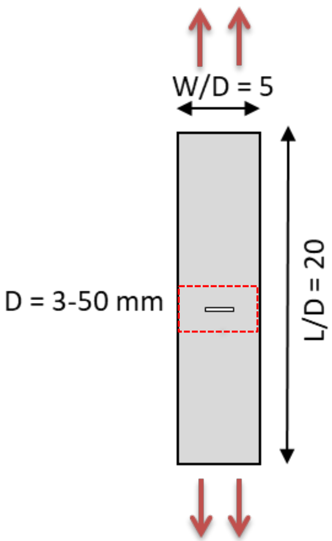
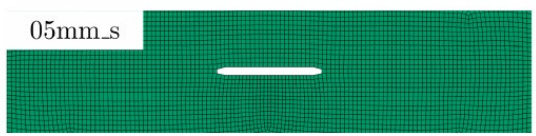
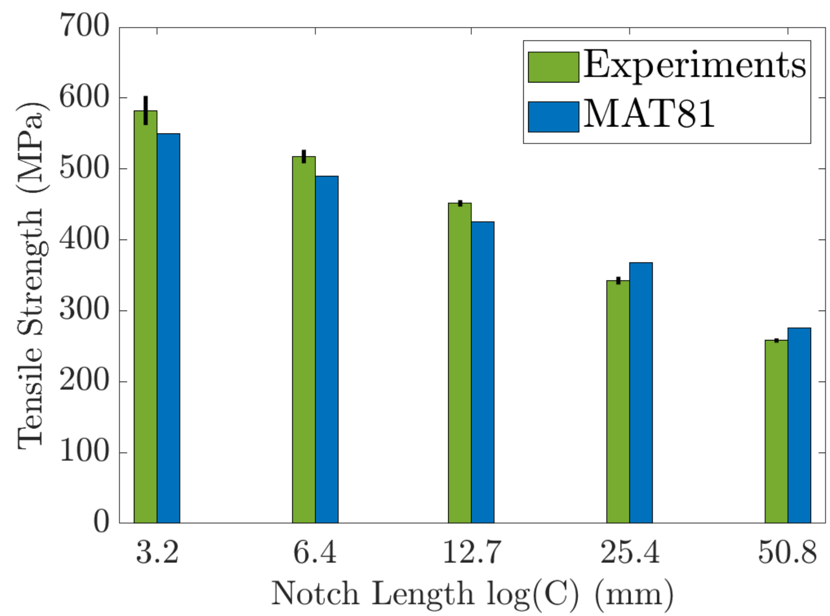
Validation – Tension

Centre-notched Tensile tests*





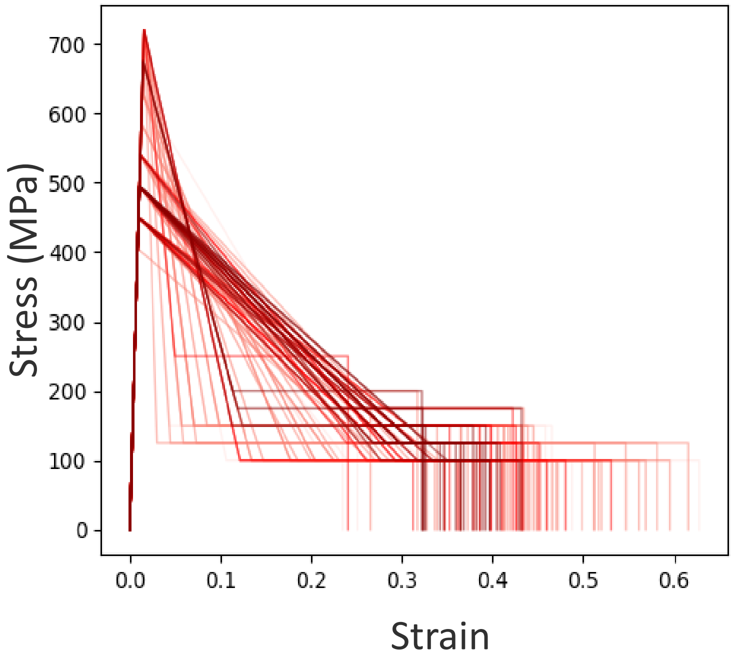
Prediction of failure in centre-notched specimens using LS-DYNA MAT81 with properties obtained by the trained Neural Network from OCT tests

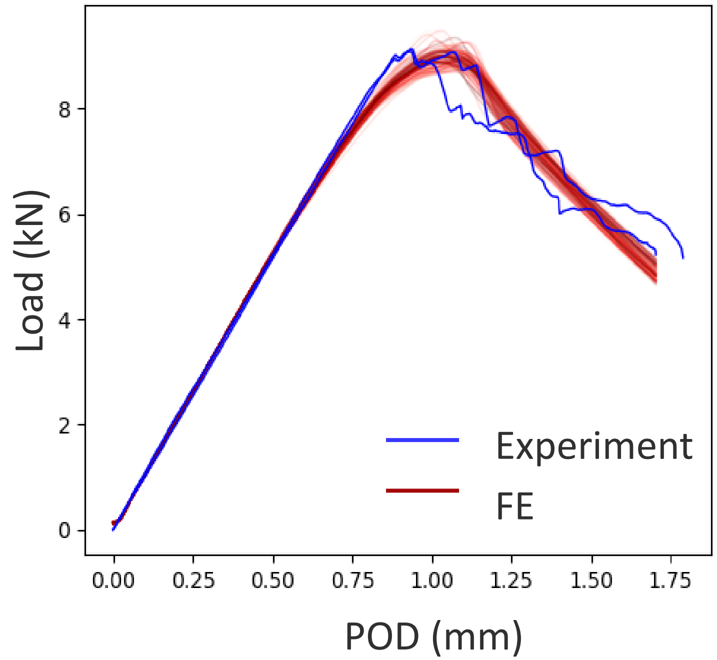


* Xu X, Wisnom MR, Li X, Hallett SR. A numerical investigation into size effects in centre-notched quasi-isotropic carbon/epoxy laminates. Compos Sci Technol 2015;111:32–9.

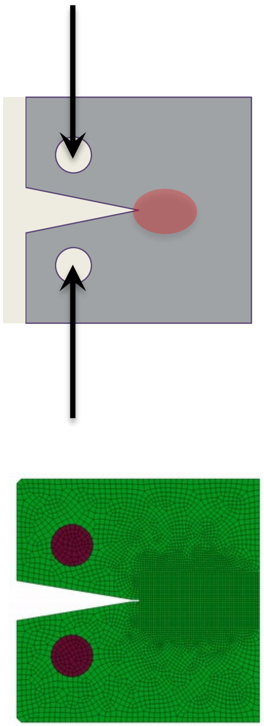
Compressive Failure Characterization

The inverse compressive failure problem is ill-posed:





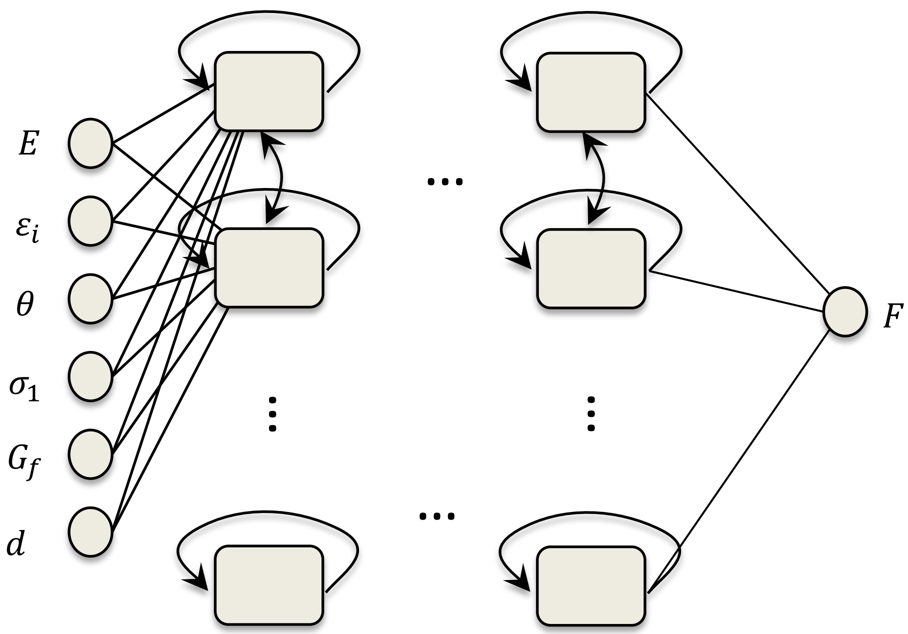
Compact Compression

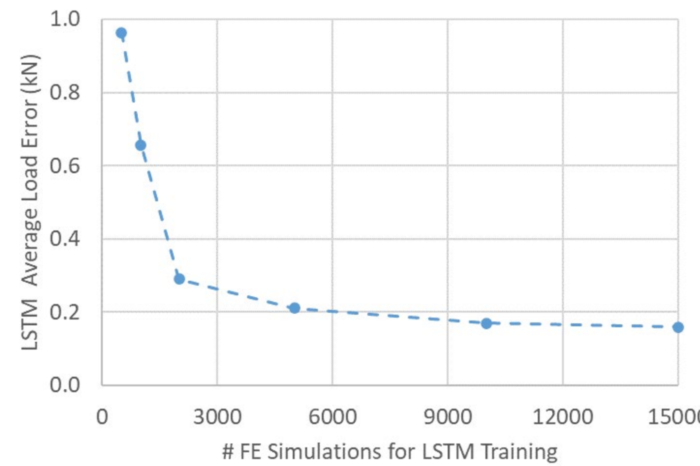


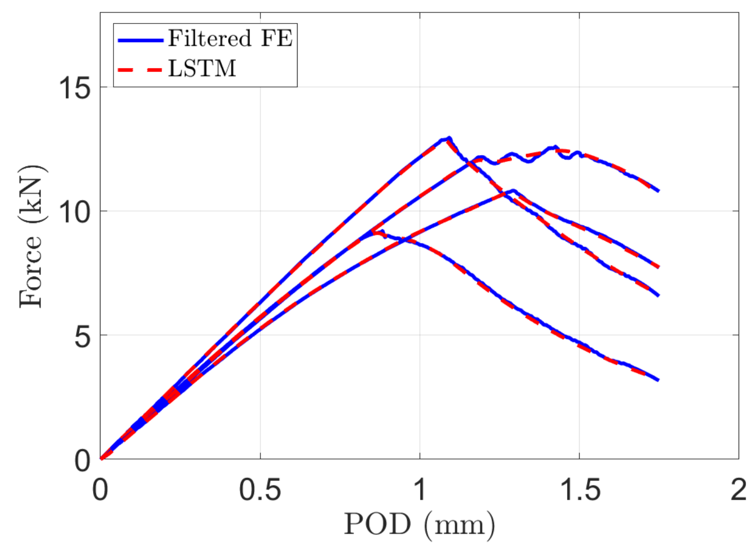
Compressive Failure Characterization

A recurrent neural networks with long short-term memory architecture (LSTM) was trained to closely replicate FE but at much higher simulation speed:

- FE: 1 simulation / 5 minutes
- LSTM: 10,000 simulations / 5 minutes







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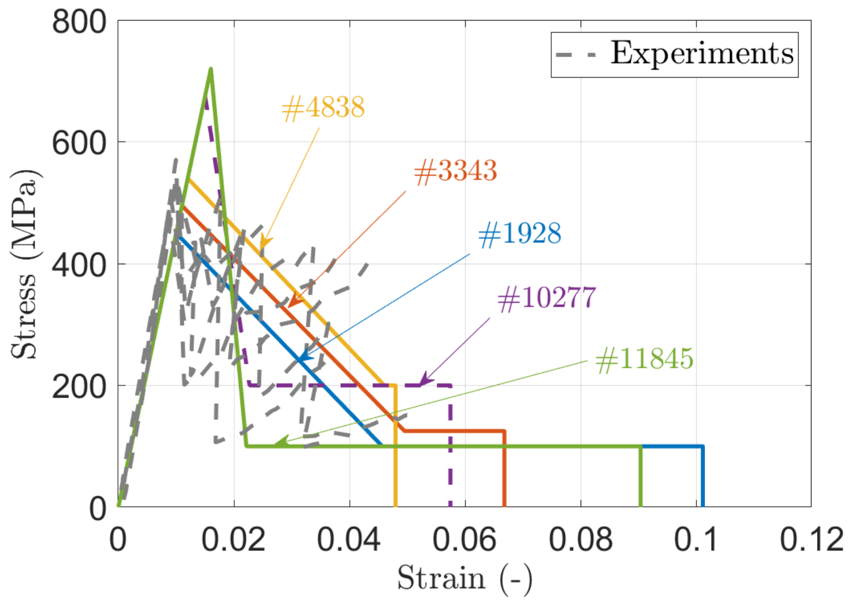
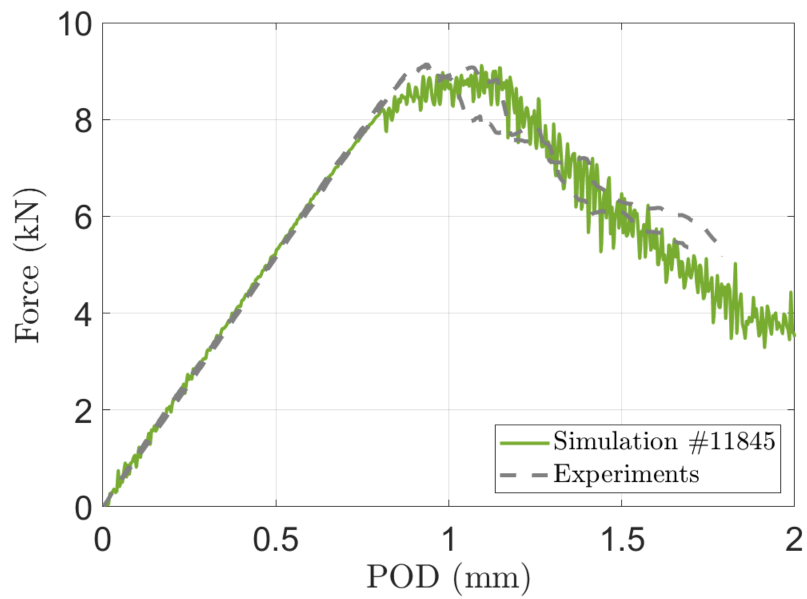
Reiner, J., Vaziri, R., & Zobeiry, N. (2021). Machine learning assisted characterization and simulation of compressive damage in composite laminates. Composite Structures, 273, 114290.

Compressive Failure Characterization

- Using fast LSTM model, 80,000 simulations were conducted in about half an hour.
- Top 5 strain-softening curves were selected to minimize overall error in FE predictions for load-displacement of CC tests.

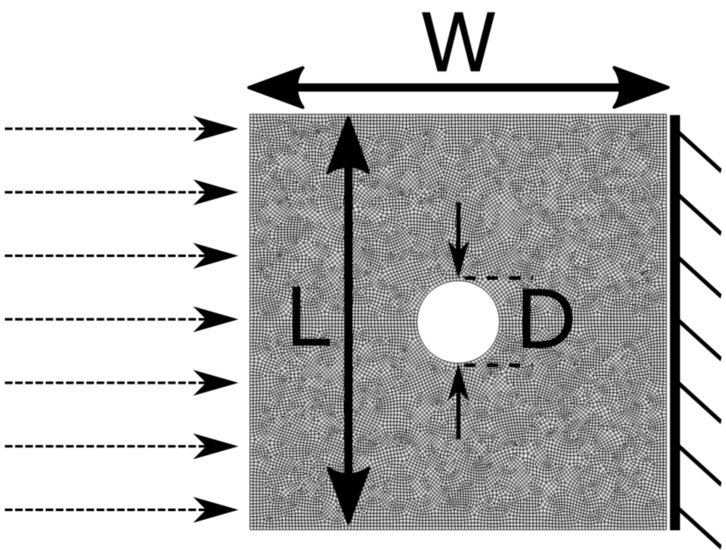


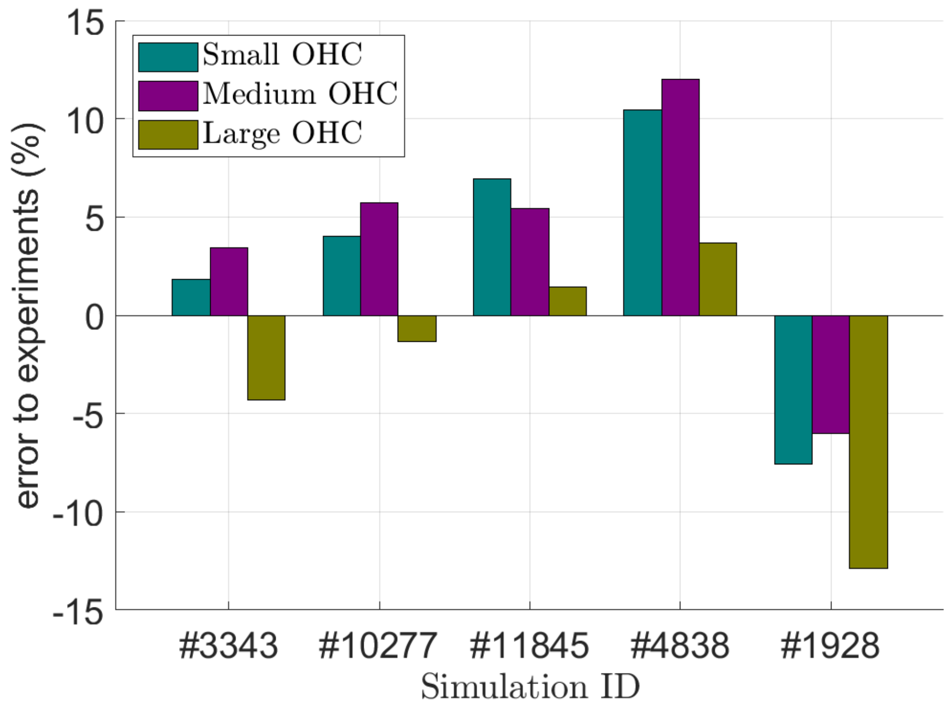


Reiner, J., Vaziri, R., & Zobeiry, N. (2021). Machine learning assisted characterization and simulation of compressive damage in composite laminates. Composite Structures, 273, 114290.

Validation – Open Hole Compression

Open-hole Compression*



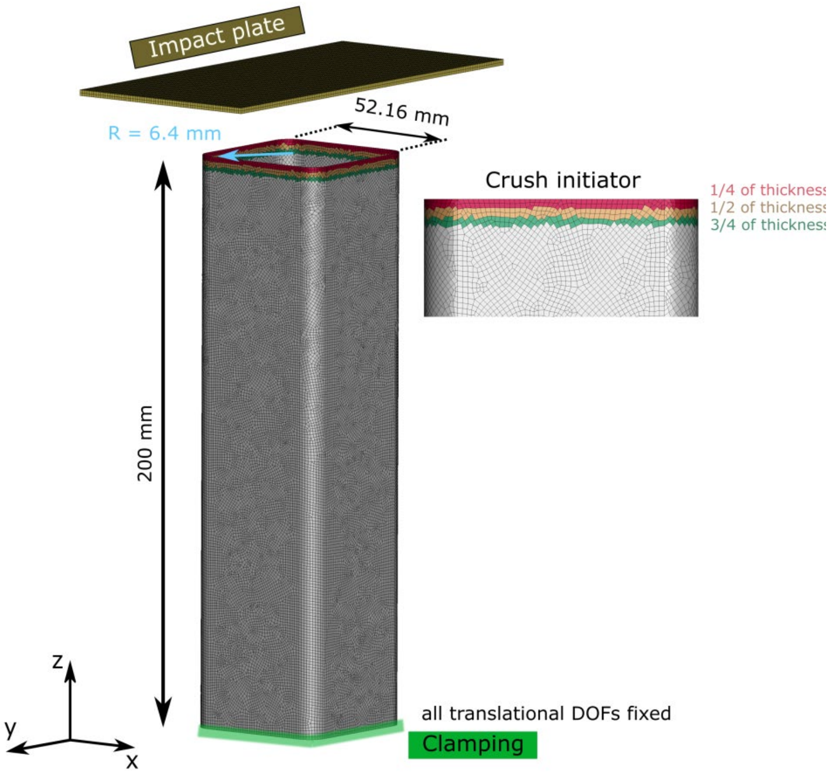


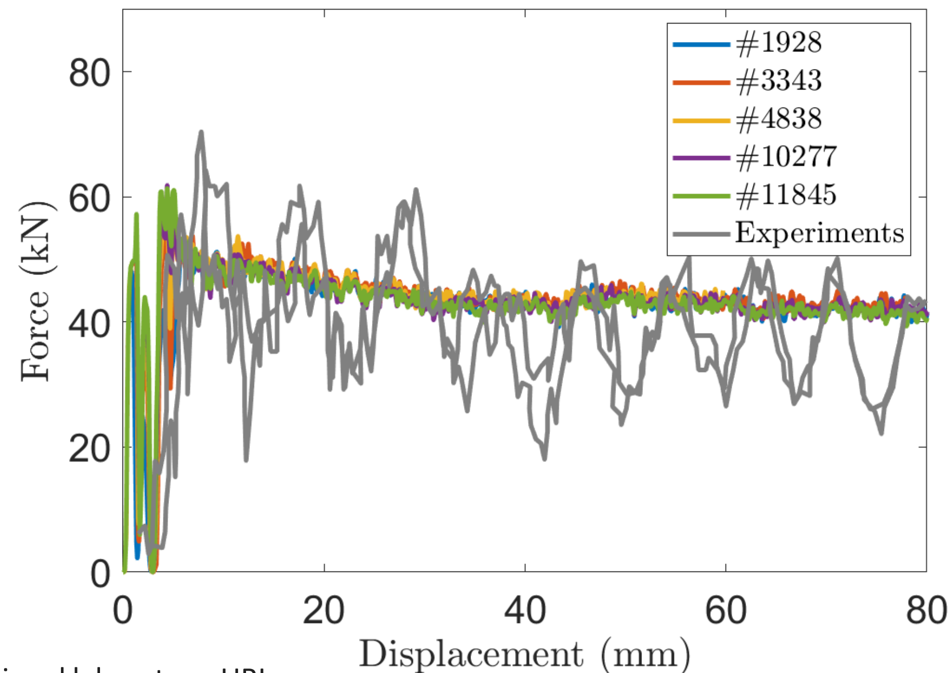
* Lee J, Soutis C. Measuring the notched compressive strength of composite laminates: Specimen size effects. Compos Sci Technol 2008;68(12):2359–66

Reiner, J., Vaziri, R., & Zobeiry, N. (2021). Machine learning assisted characterization and simulation of compressive damage in composite laminates. Composite Structures, 273, 114290.

UBC CRN Composites Research Network

Validation – Tube Crushing





* Crashworthiness of Carbon Fiber Composites, Oak ridge national laboratory. URL: http://energy.ornl.gov/CFCrush/rate_tests/rate_tests.cgi..

Reiner, J., Vaziri, R., & Zobeiry, N. (2021). Machine learning assisted characterization and simulation of compressive damage in composite laminates. Composite Structures, 273, 114290.

Calibration – Physics Informed Neural Network

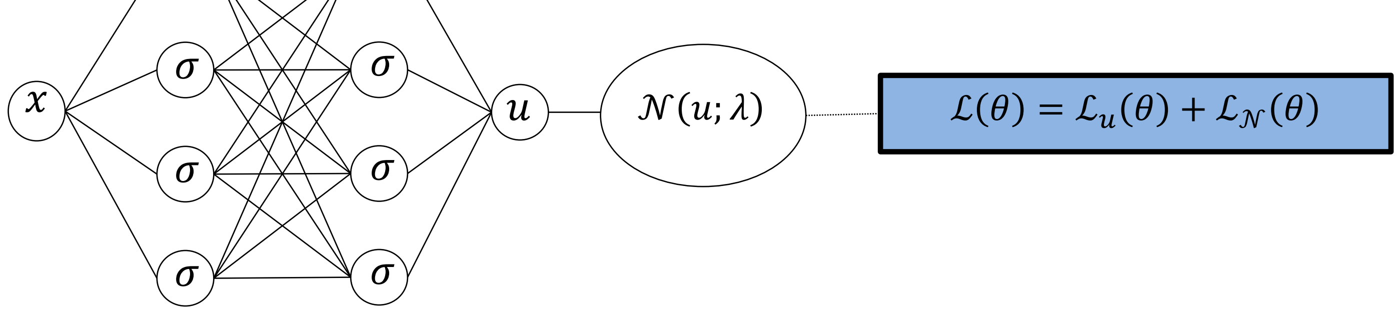
PINN: methods in machine learning for incorporating the prior knowledge of the problem into the neural network (NN) algorithm so that minimal data is needed for its training [1].

Applications:

- Forward problems - Solving ODEs and PDEs
- Inverse problems - Finding parameters of the ODEs/PDEs

$\mathcal{N}(u;\lambda) = Nonlinear\ operator$ with parameters λ $to\ be\ characterized$

$\theta =$ PINN $parametrs\ to\ be\ fine\text{–}tuned$



[1] M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," J. Comput. Phys., 378, pp. 686–707, (2019)

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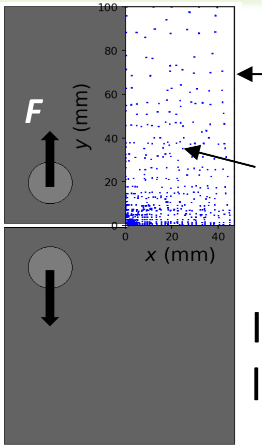
Application of PINN - Virtual OCT Test

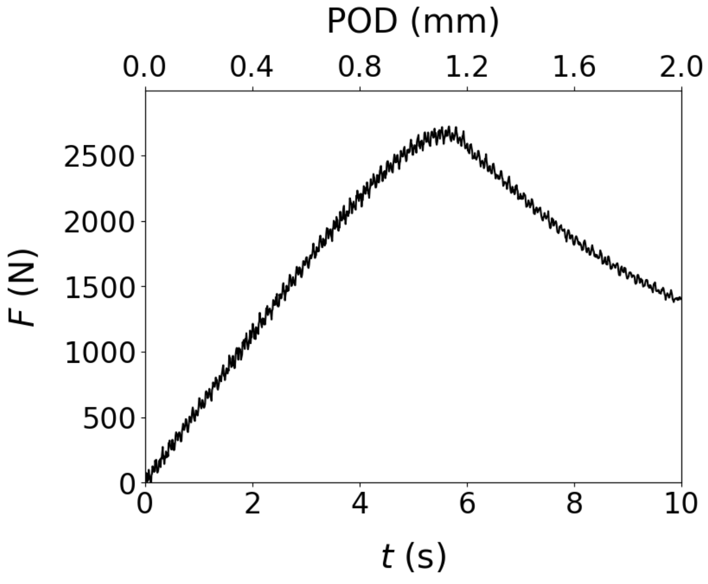
FE simulations of OCT test used to generate synthetic DIC and global force data as "ground truth" data for material property identification.

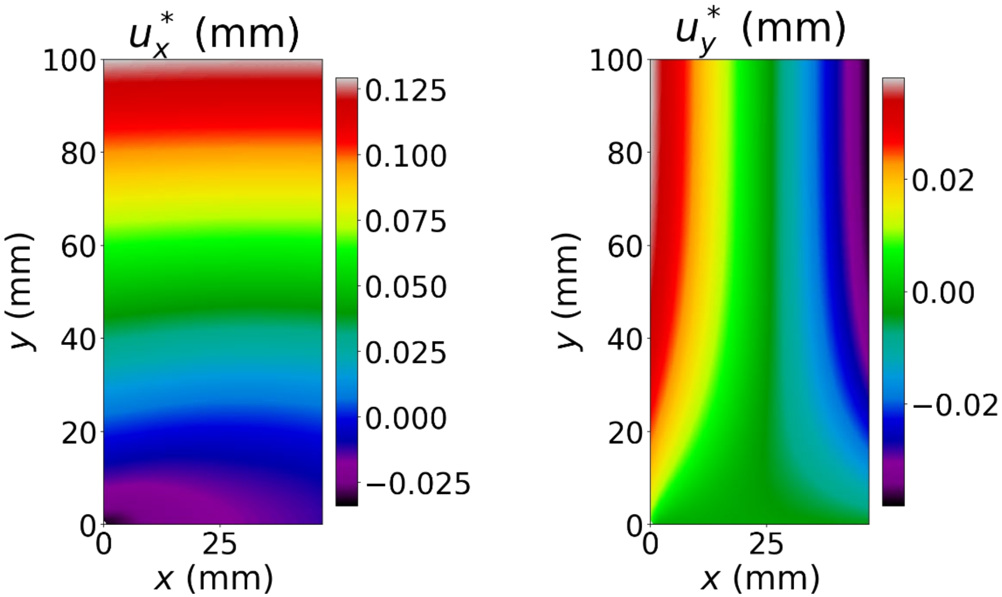


IM7/8552 CFRP laminate

Synthetically generated data used for PINN training consists of time histories of:

- displacement fields: $u_x(t), u_y(t)$
- global force: $F(t)$



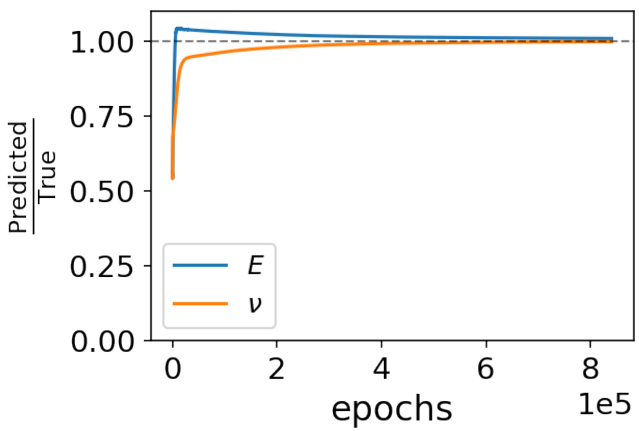


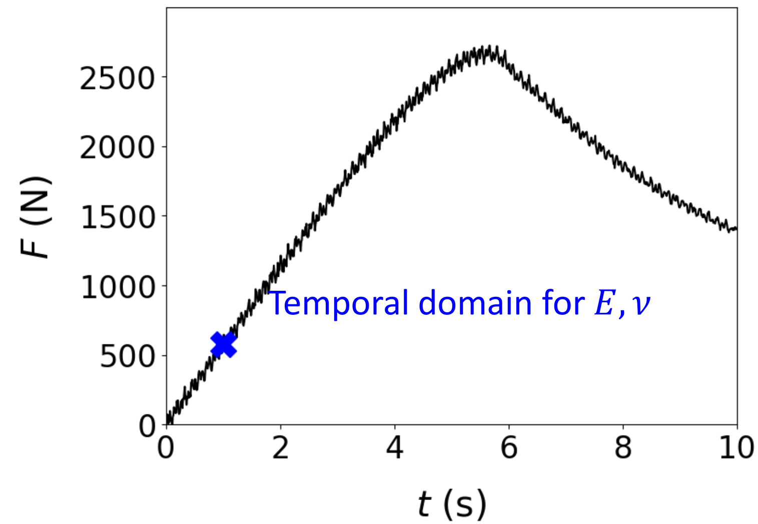
Displacement field at t = 1 s

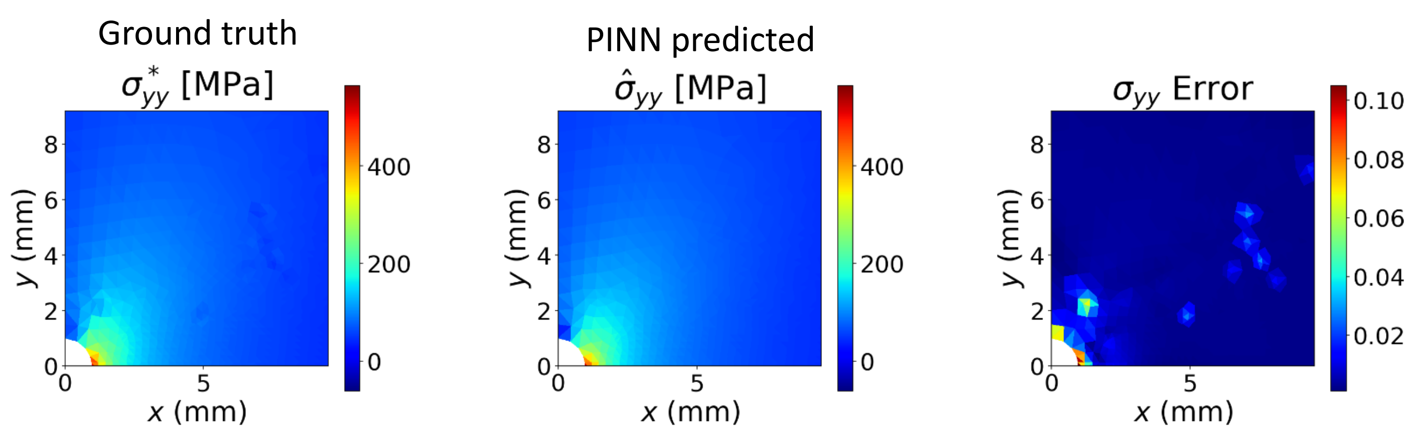
Characterization Results - Elastic Constants

Elastic parameters E, ν are identified using a timestep at early stages of loading

Evolution of the elastic properties during training







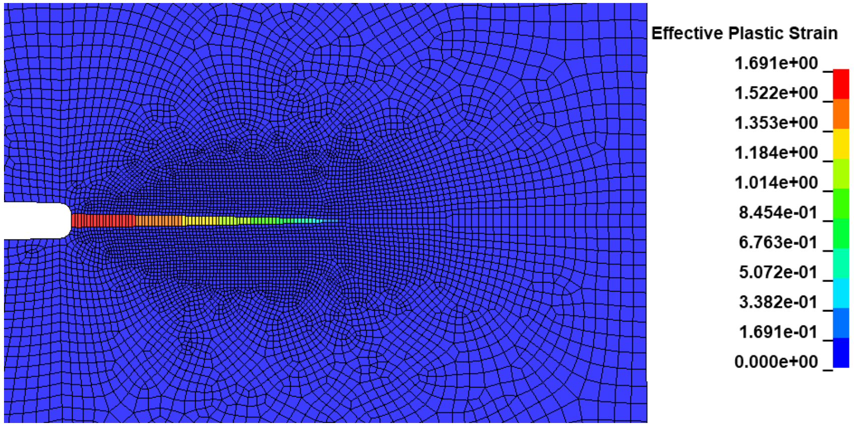
Predicted stress field along y direction at t = 1s over a small subdomain

Characterization of Damage Parameters : A Pipeline Approach

Damage parameters σ_i, $\bar{\epsilon}_{ps}$ are identified in two sequential training stages, using the timesteps sampled from the nonlinear response in the pre-peak and post-peak regimes.

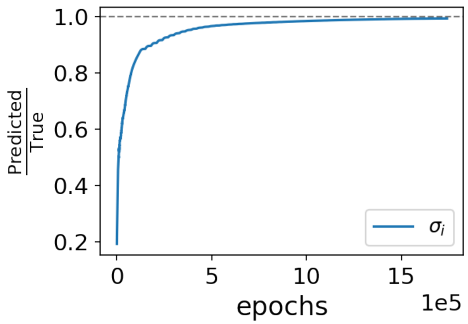
In the nonlinear regime, localization is observed in FE simulations. **A pipeline of networks** is proposed to deal with localization:

1. A forward data driven NN is used to predict displacement and strain fields
2. An inverse PINN is used to extract damage parameters from the strain field predicted in step 1.

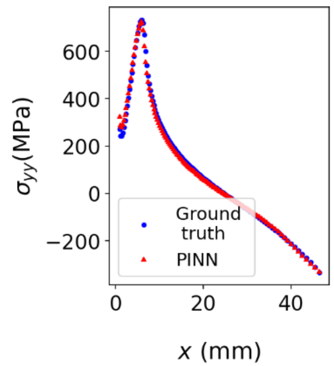


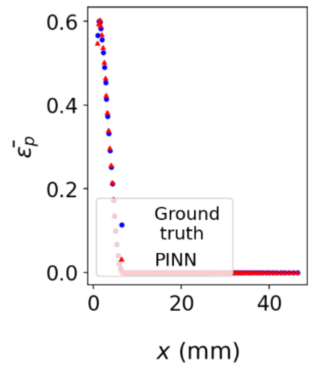
Characterization Results - Damage Parameters

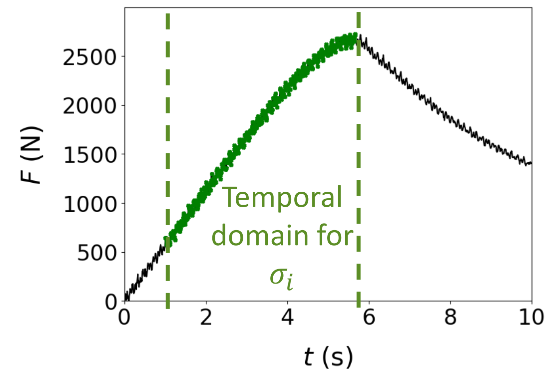
Evolution of σ_i during training



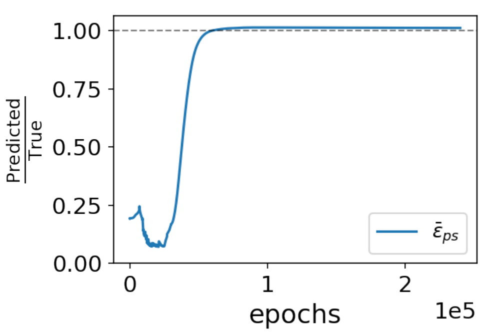
Predicted stress and effective plastic strain at t = 5.5 s in the local zone (where $x \in [0,46]\ mm, y = 0$)



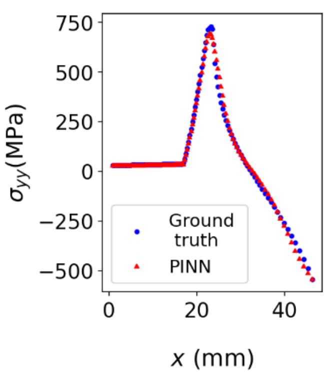


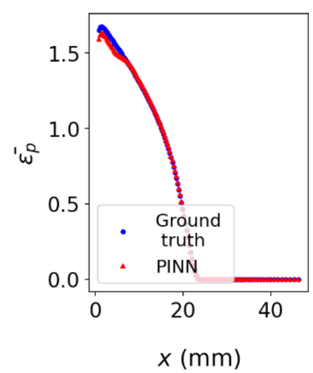


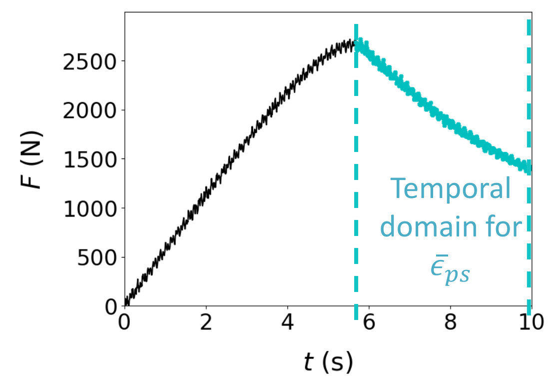
Evolution of $\bar{\epsilon}_{ps}$ during training



Predicted stress and effective plastic strain at t = 10 s in the local zone (where $x \in [0,46]\ mm, y = 0$)







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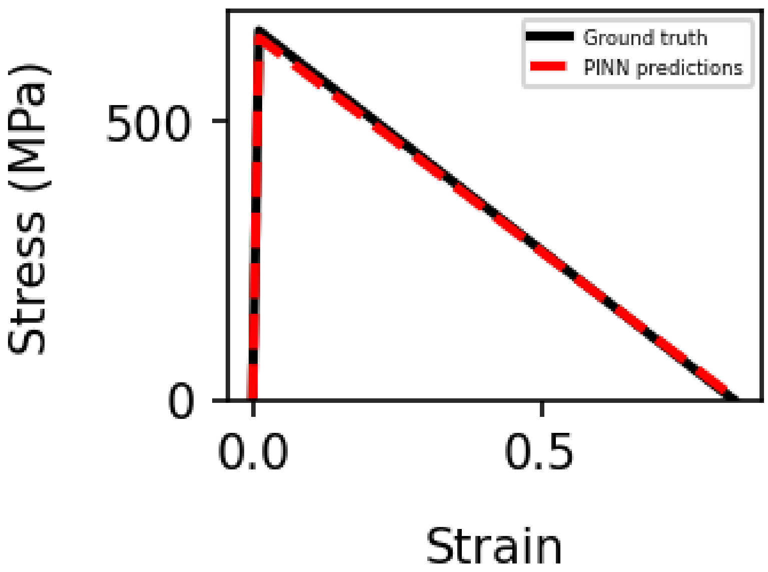
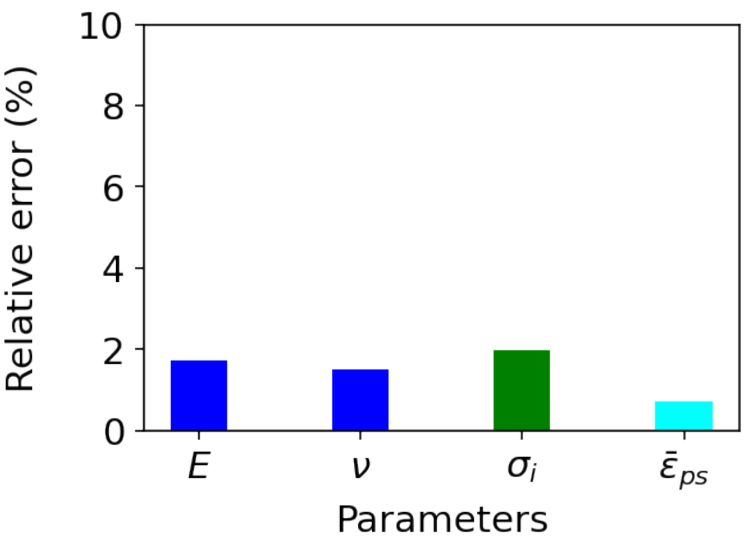
Constitutive Model Characterized using PINN

Comparison of strain-softening curves: PINN-inferred vs. ground truth (i.e.input stress-strain curve used for FE simulation of OCT test)



Error (%) for key parameters of the strain-softening constitutive response



E. Haghighat, S. Abouali, R. Vaziri, Constitutive model characterization and discovery using physics-informed deep learning, Engineering Applications of Artificial Intelligence 120 (2023) 105828.33

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Summary and Conclusions

- Simulation of progressive damage and failure response of composite materials/structures rely on sufficiently high quality experimental data that are used to quantify the input parameters of constitutive models, typically in the form of strain-softening curves
- Quality of the predictions depend largely on the accuracy of the constitutive model in representing the physical material behaviour which is driven more so by how well the model is characterized (calibrated) than the details incorporated in the constitutive model formulation
- Typically FE calibration approach is based on time consuming tests, complex data reductions, and trial-and-error FE analyses
- Theory-guided machine learning (TGML) and Physics-Informed Neural Networks (PINN) can be used effectively for inverse modeling and calibration of input parameters of FE models in a more objective manner
- The combination of science-based simulation (FEA) and data-driven modelling (ML) when combined with robust statistical sampling techniques can enable large-scale composite components to be analysed virtually considering inherent uncertainty of composites

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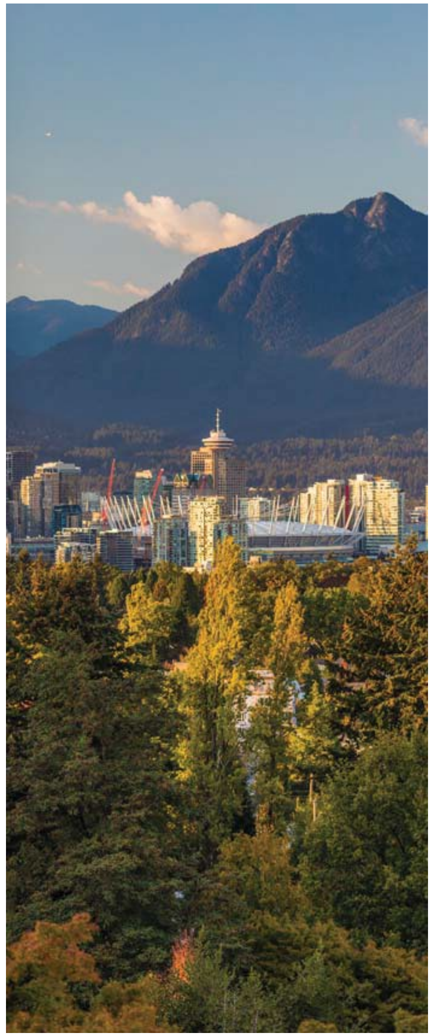
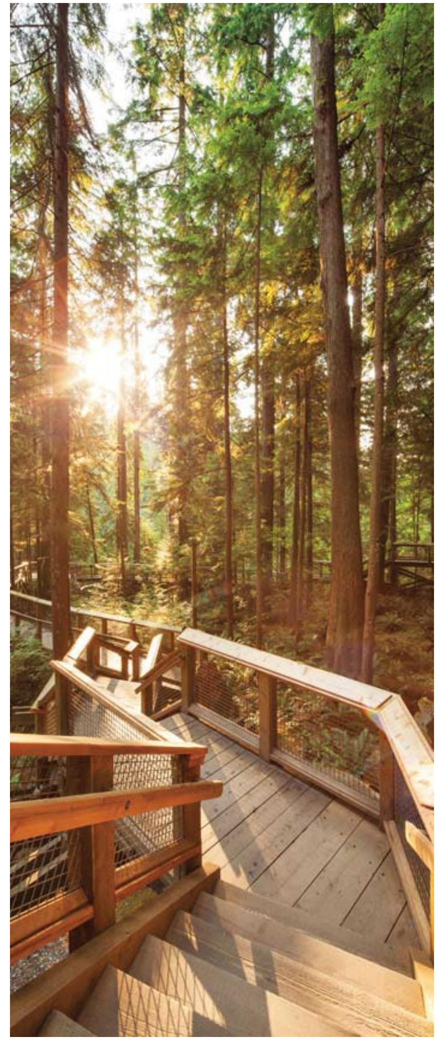

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