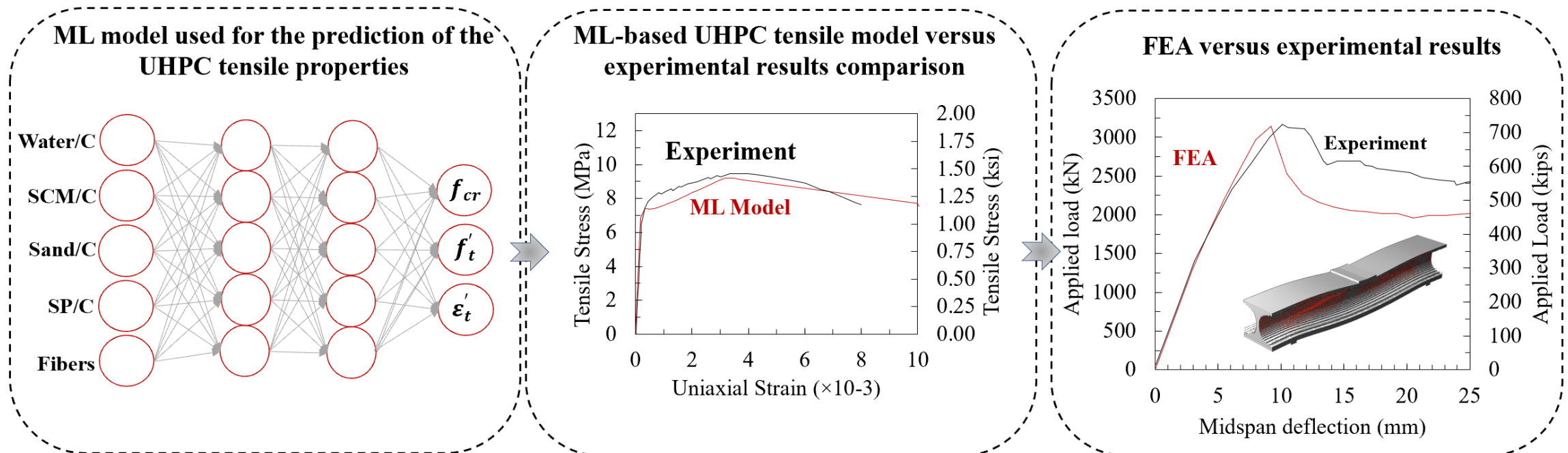


Synergizing machine learning and nonlinear finite element analysis to simulate the behavior of UHPC members



Amjad Diab
Anca Ferche

Outline

**UHPC
OVERVIEW**

**MODELING
APPROACH**

**MODELING
VALIDATION**

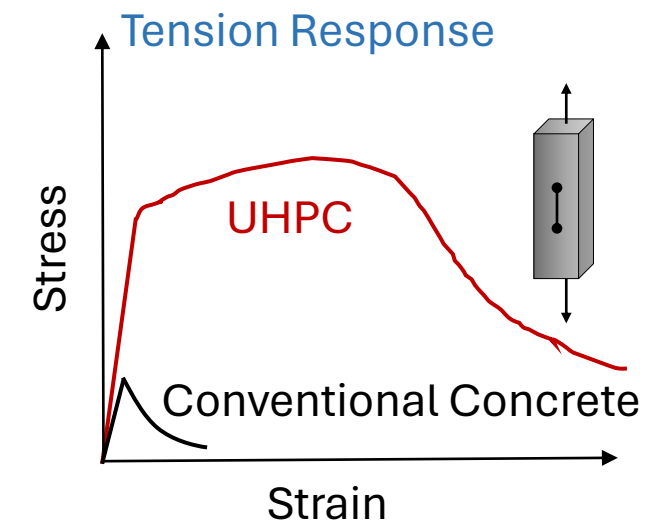
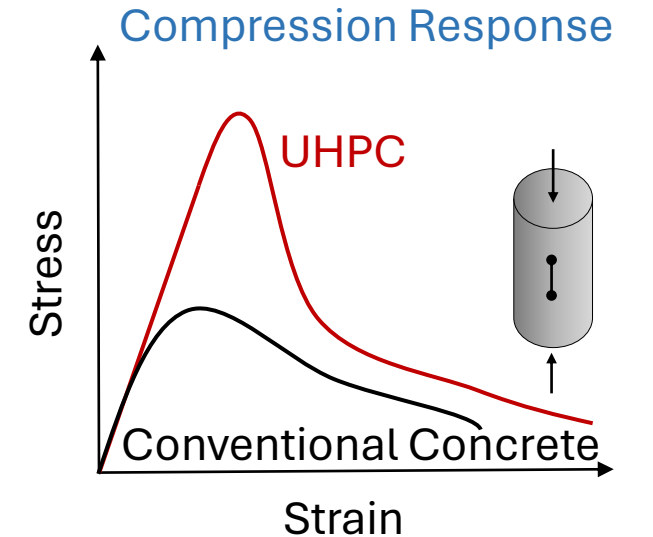
CONCLUSIONS

Introduction

Ultra-High Performance Concrete (UHPC) is a cementitious composite with a discontinuous pore structure, incorporating steel fiber reinforcement.

UHPC characteristics:

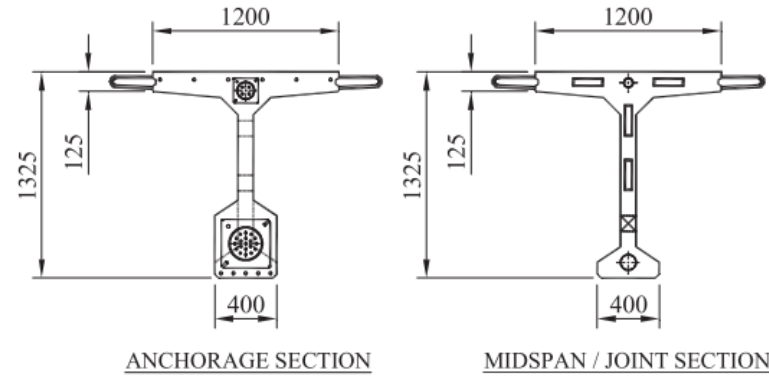
- high compressive strengths (~120-250 MPa),
- high tensile strengths (~6-16 MPa),
- superior post-cracking ductility compared to other cementitious composites,
- excellent crack control,
- self-consolidating workability,
- superior durability.



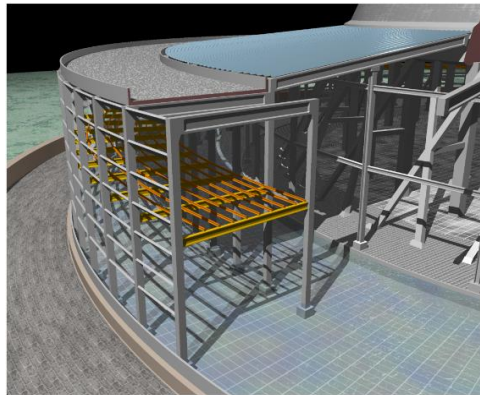
UHPC Applications



Pi section bridge girder



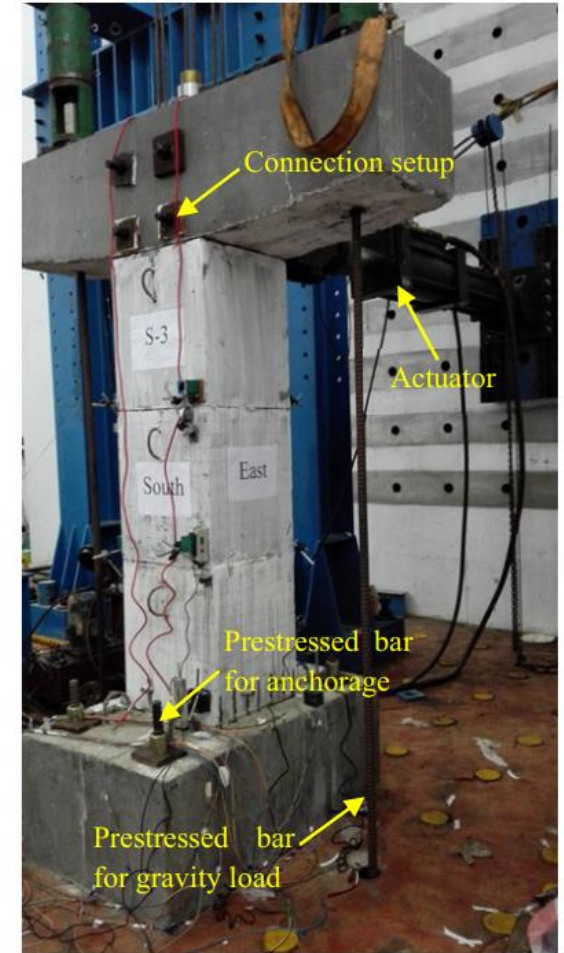
Sungai Nerok segmental bridge girder



Cattenom power plant



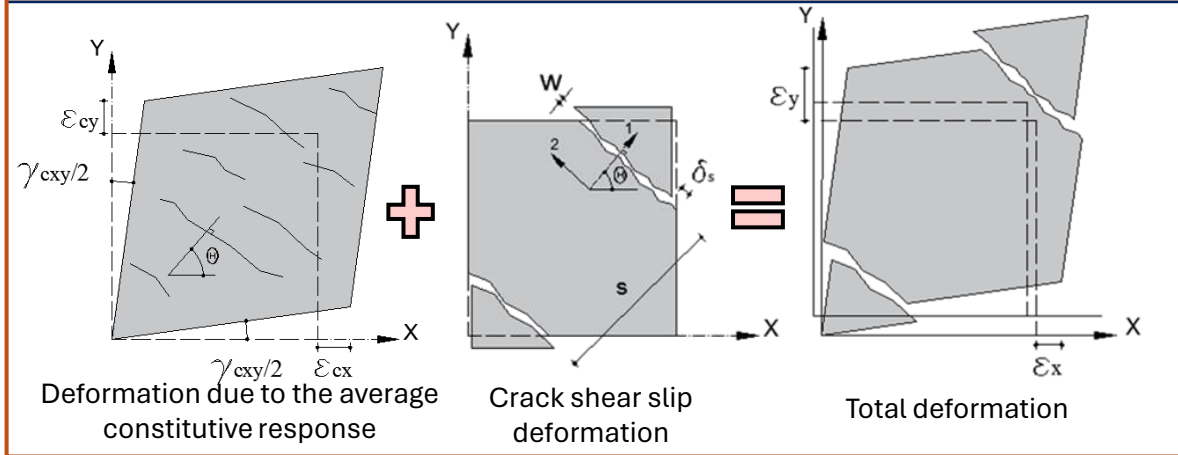
Offshore wind turbine foundations



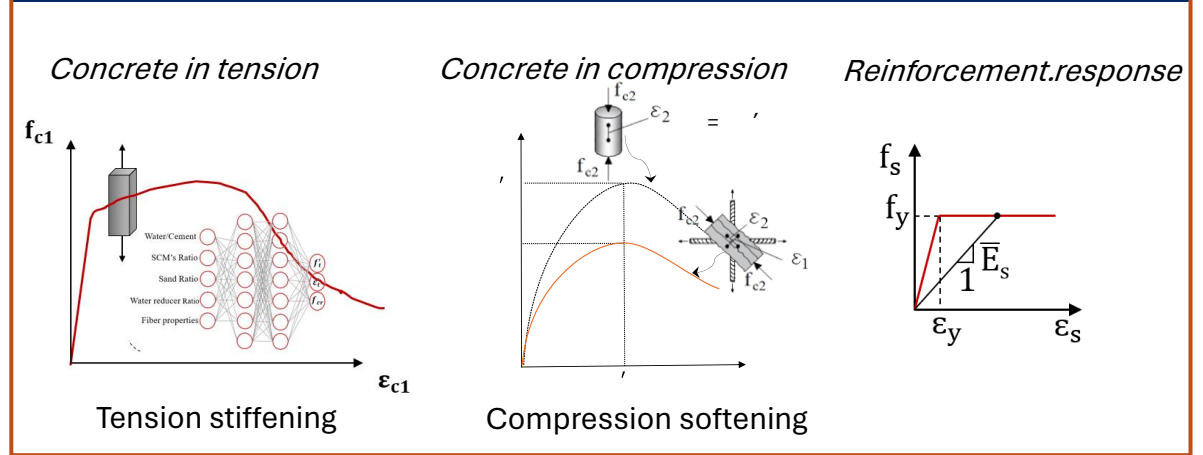
Segmental bridge columns

Modeling Approach

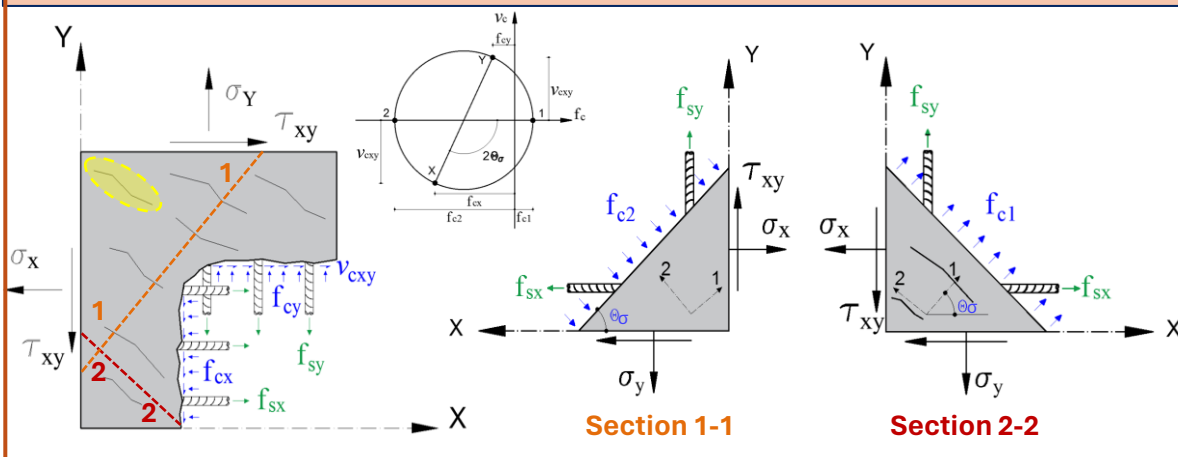
Compatibility requirements



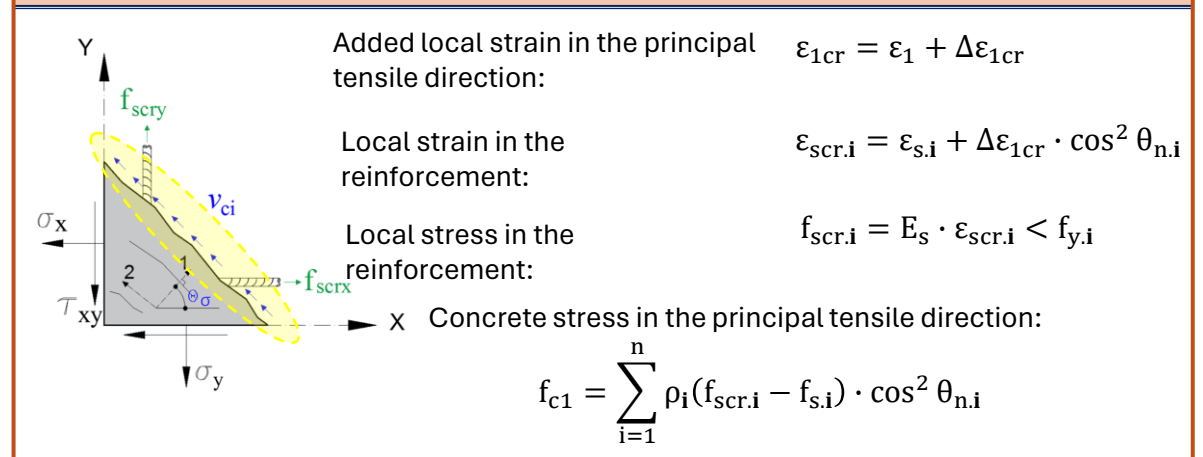
Constitutive relationships



Equilibrium in terms of average stresses

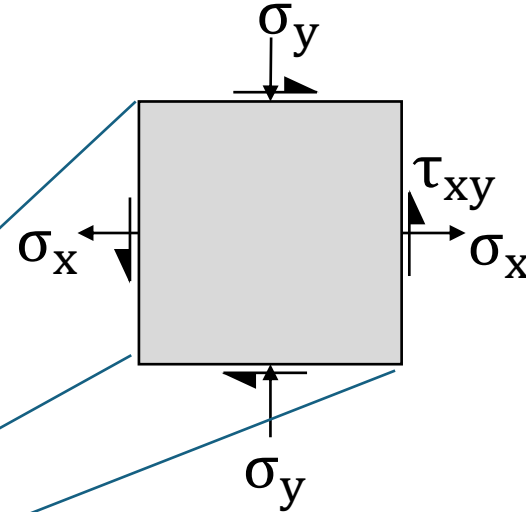
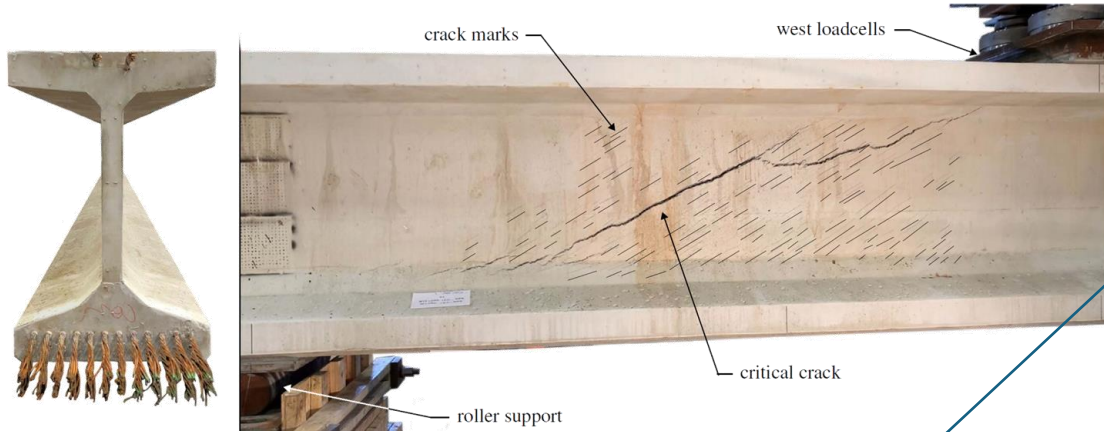


Equilibrium in terms of local stresses at a crack



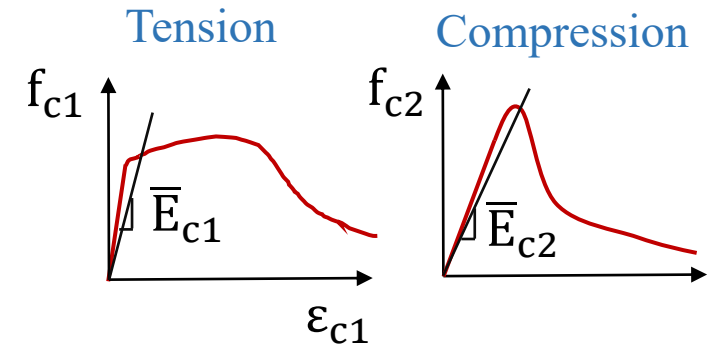
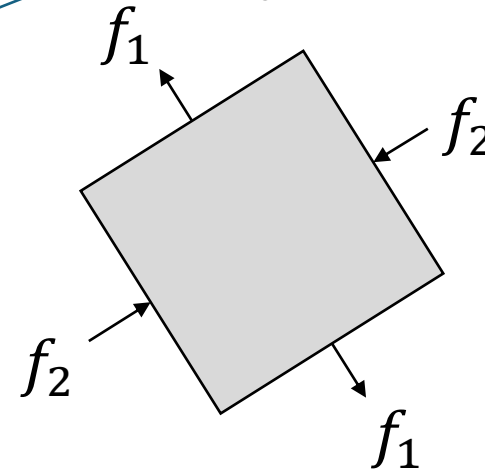
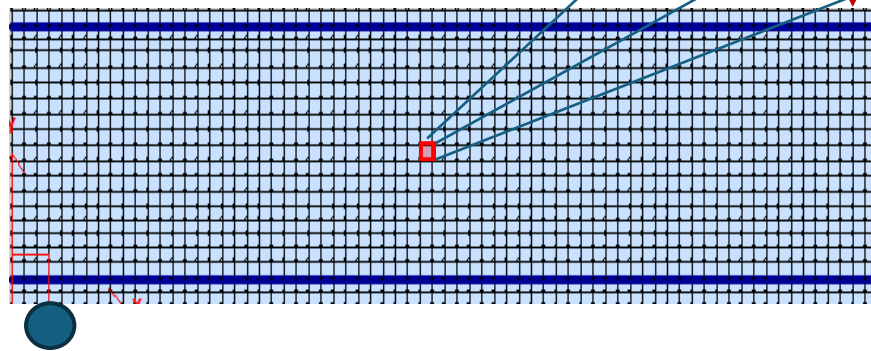


Modeling Approach



$$[D_c]' = \begin{bmatrix} \bar{E}_{c1} & 0 & 0 \\ 0 & \bar{E}_{c2} & 0 \\ 0 & 0 & \bar{G}_c \end{bmatrix}$$

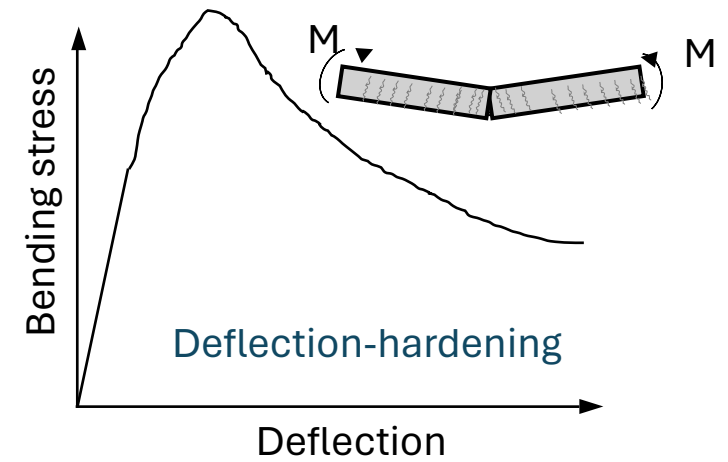
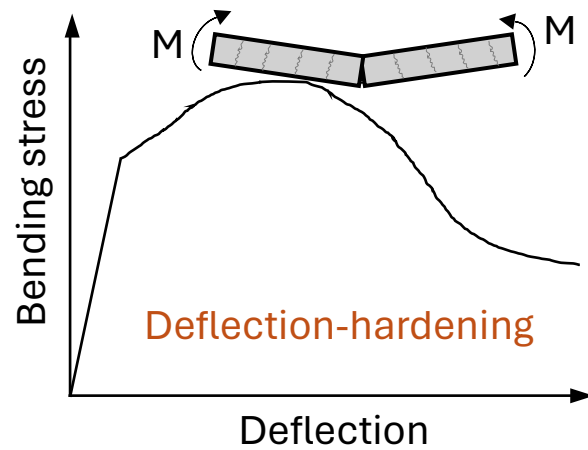
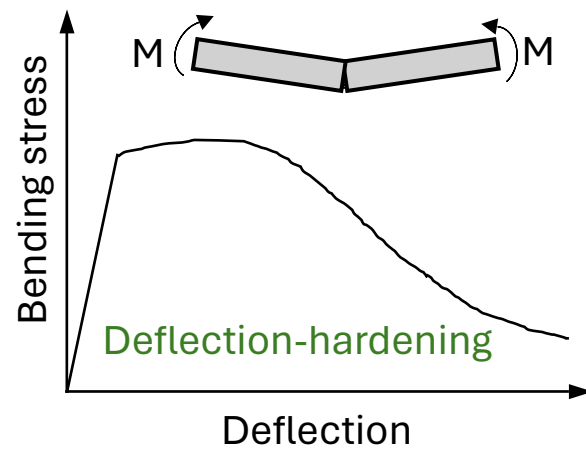
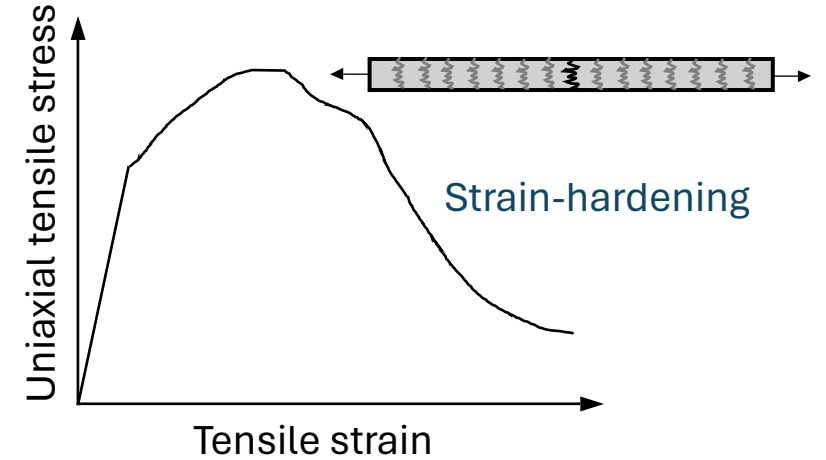
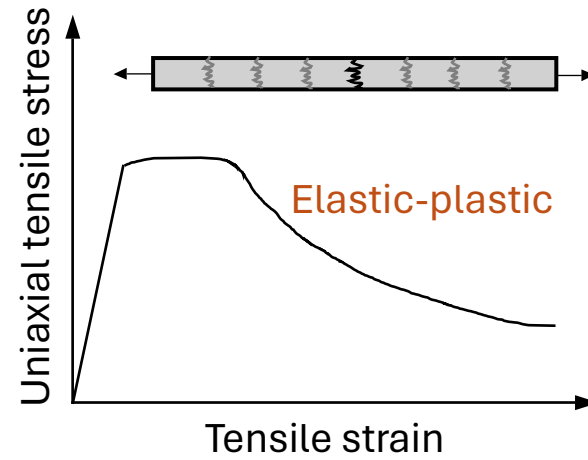
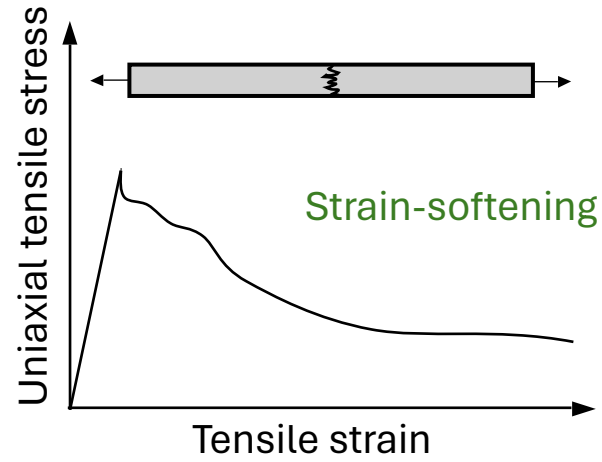
$$\bar{E}_{c1} = \frac{f_{c1}}{\epsilon_{c1}} \quad \bar{E}_{c2} = \frac{f_{c2}}{\epsilon_{c2}}$$



$$\bar{G}_c = \frac{\bar{E}_{c1} \cdot \bar{E}_{c2}}{\bar{E}_{c1} + \bar{E}_{c2}}$$



UHPC Tension Response



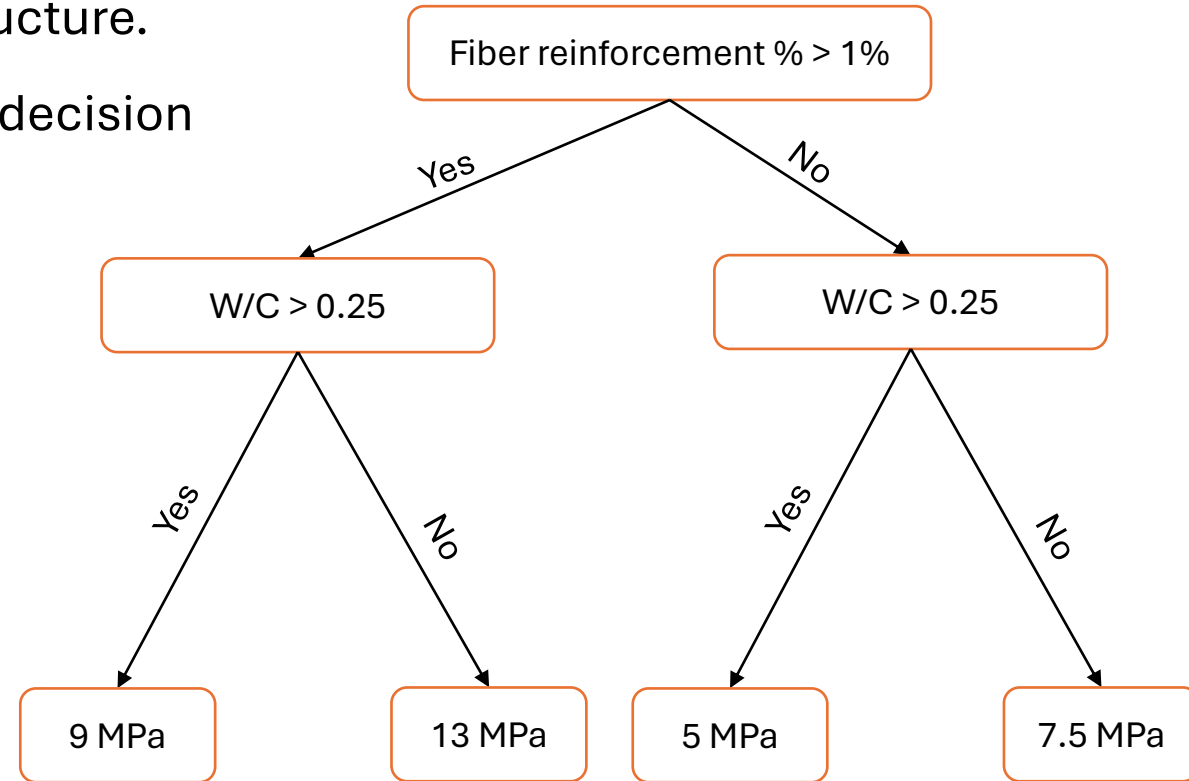
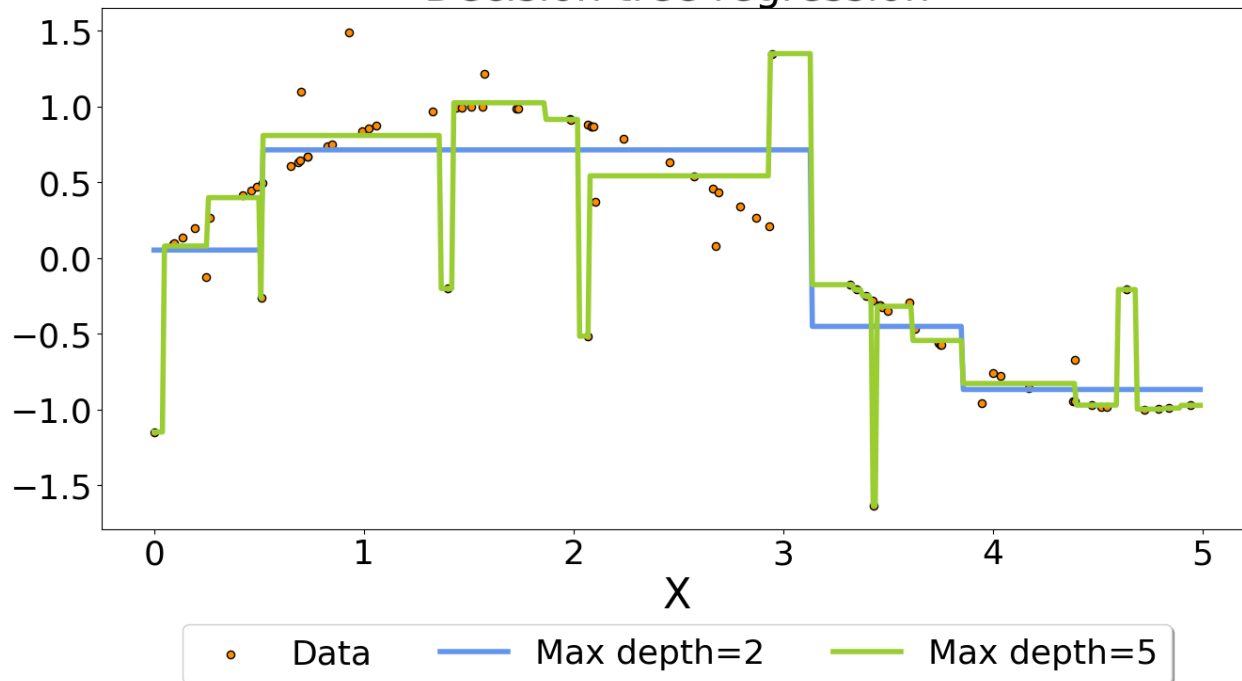
UHPC Direct Tension Database



Regression Decision Trees

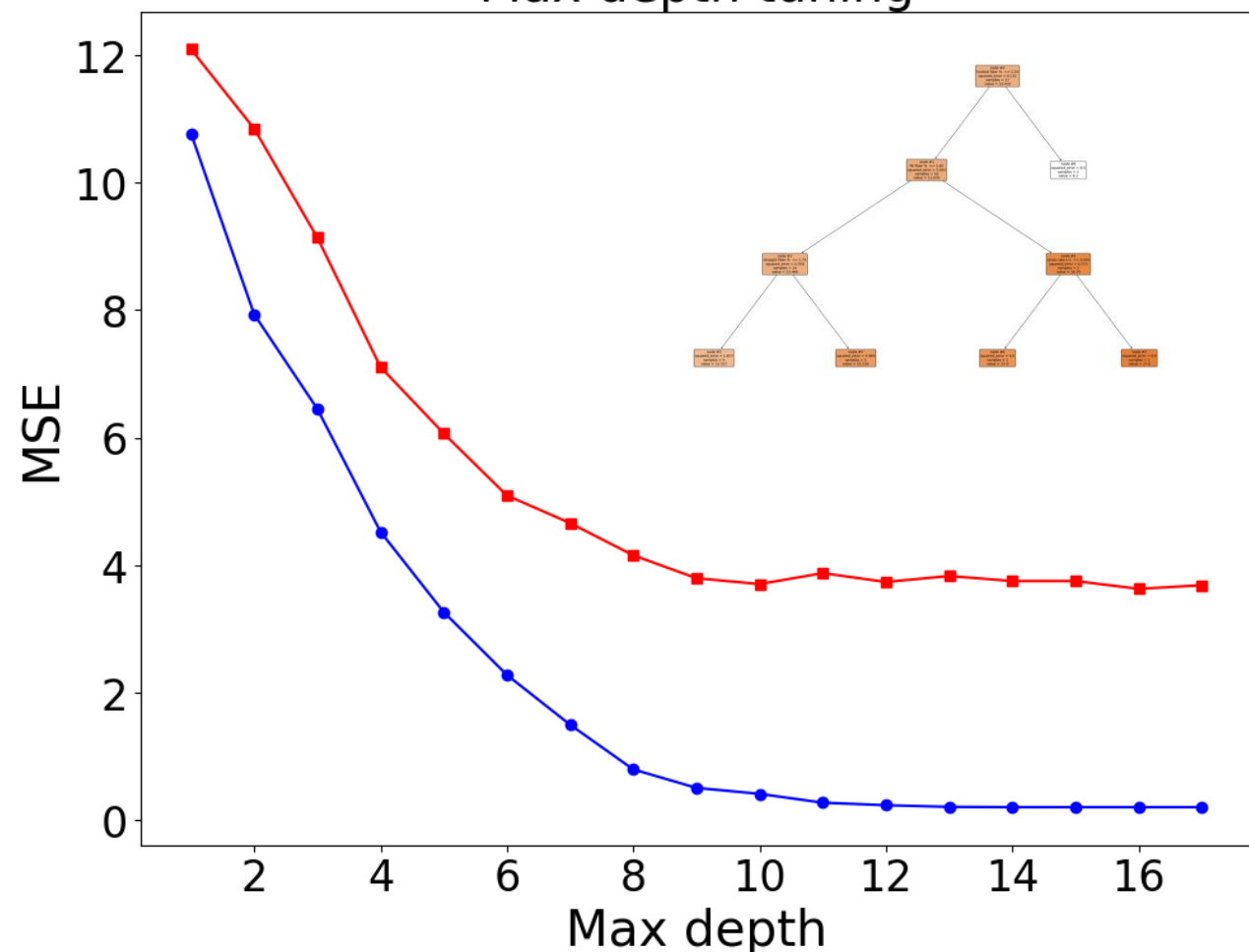
- RDT builds regression models in the form of a tree structure.
- RDT breaks down a dataset into smaller subsets with decision nodes and leaf nodes.

Decision tree regression

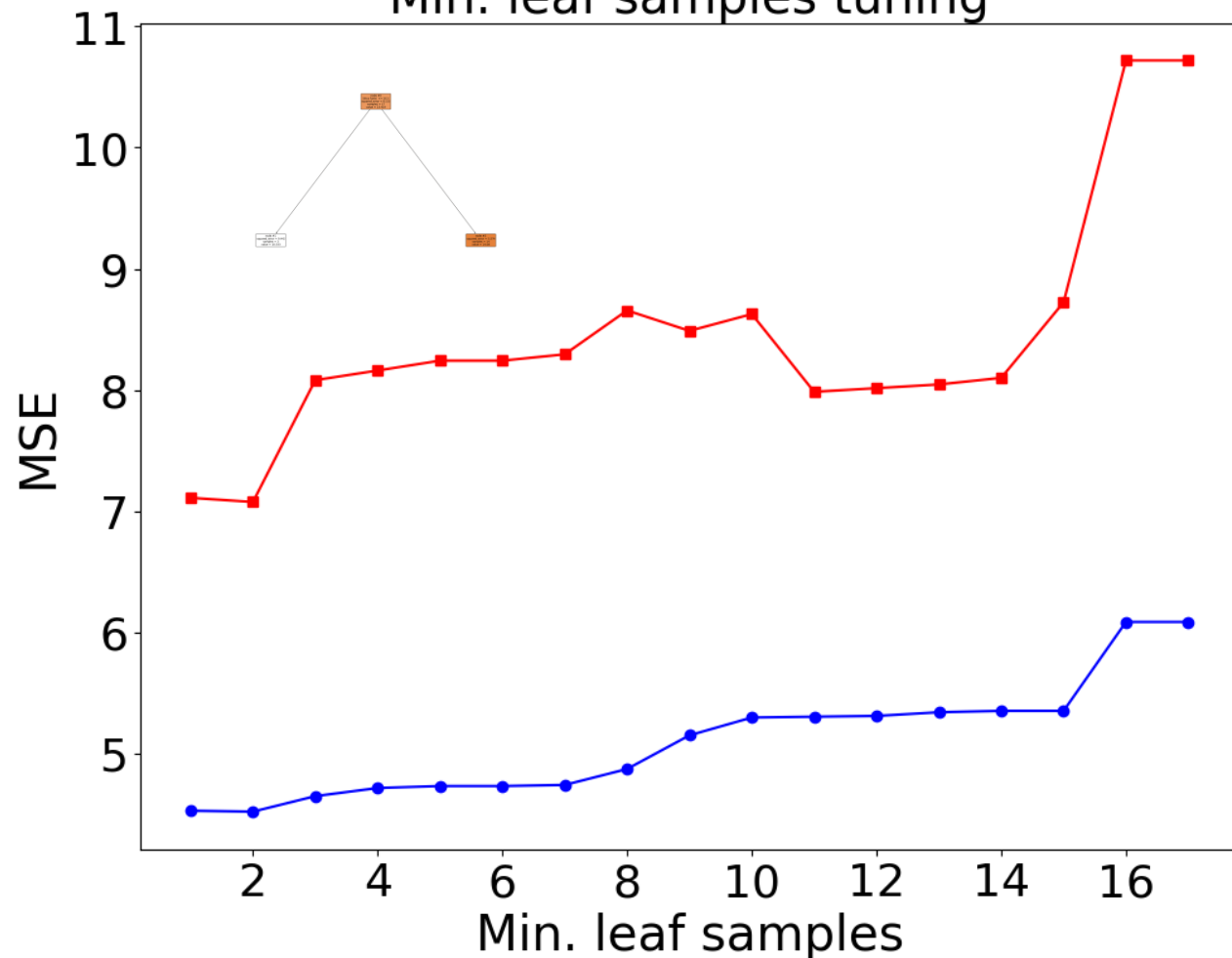


RDT Parameter Tuning

Max depth tuning



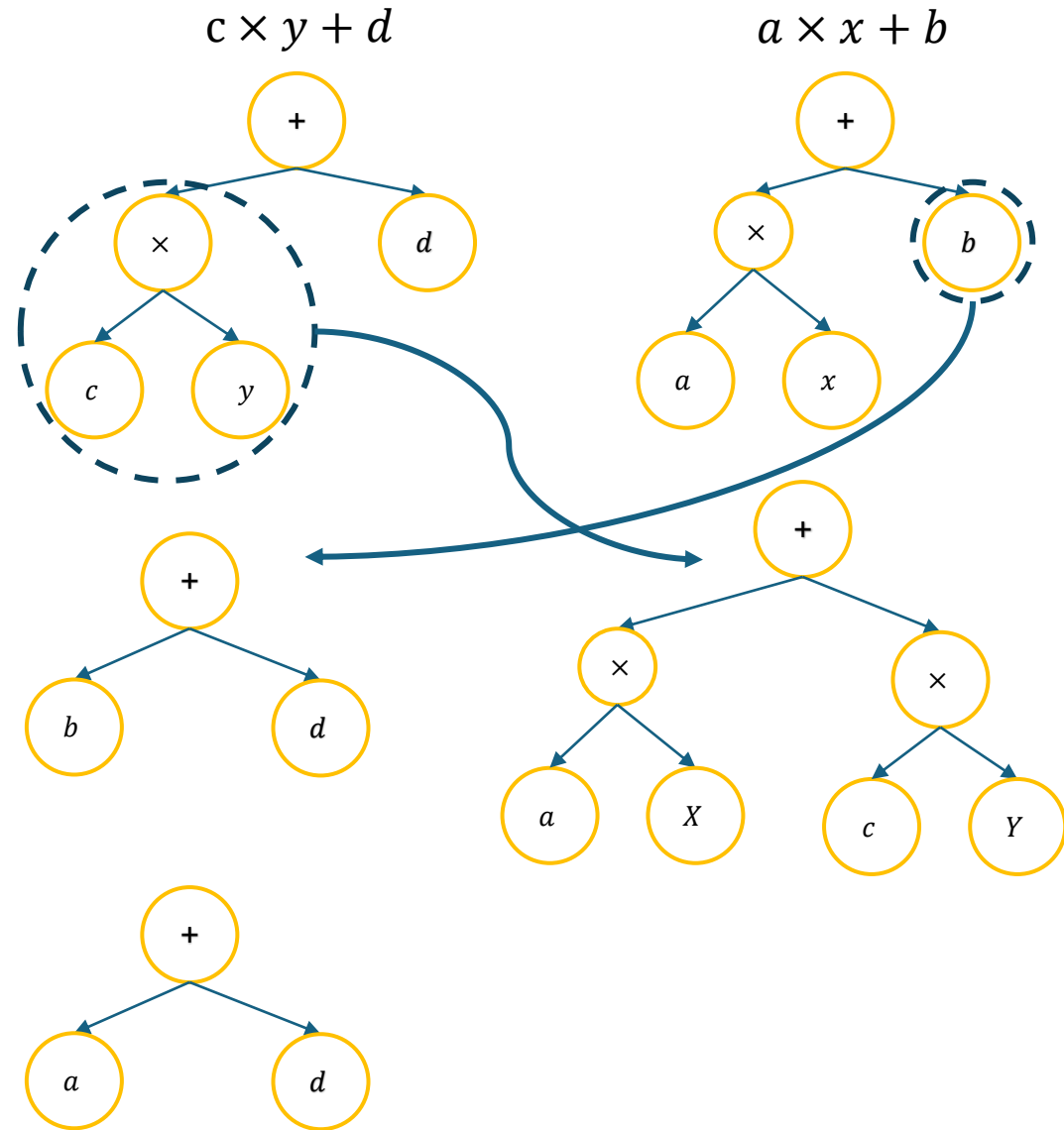
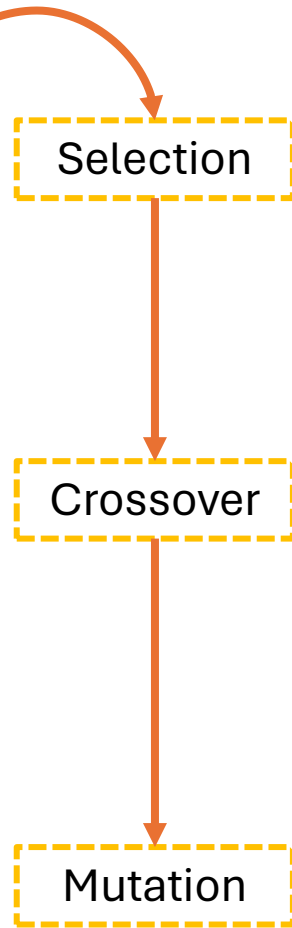
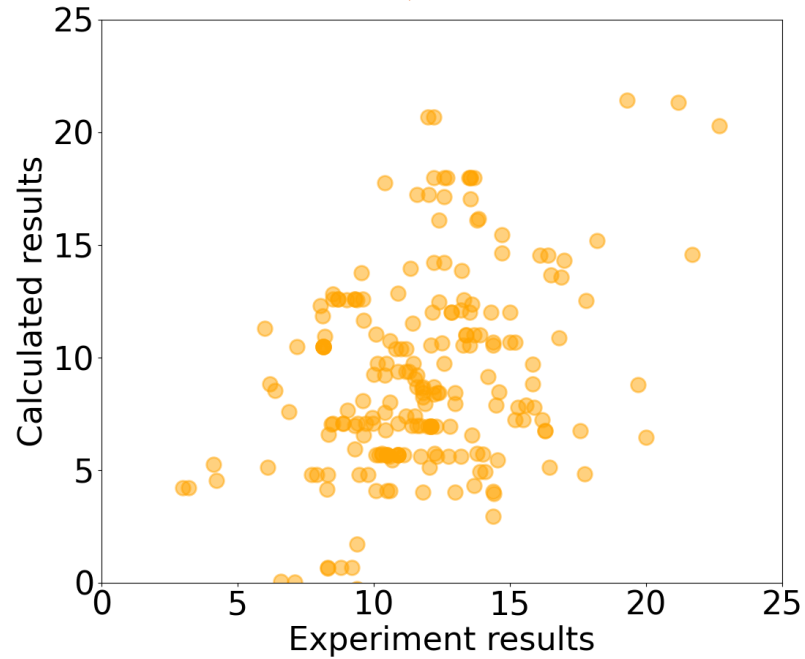
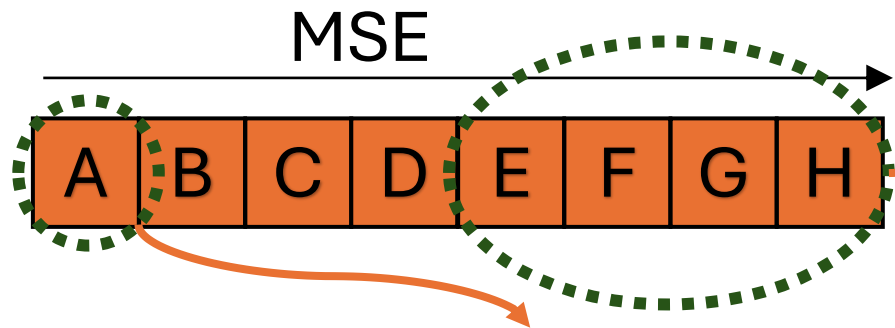
Min. leaf samples tuning



—●— Training MSE —■— Testing MSE

—●— Training MSE —■— Testing MSE

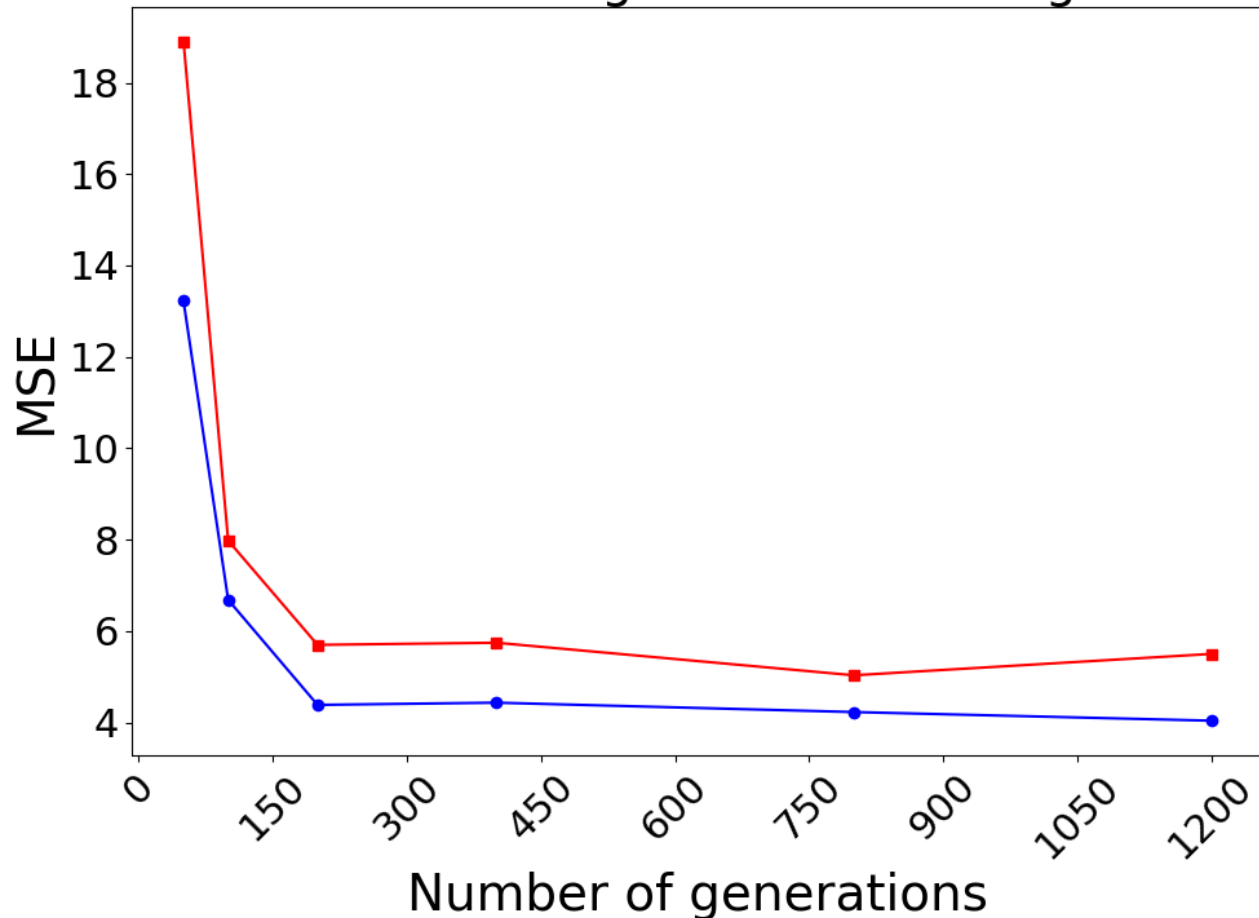
Genetic Algorithm



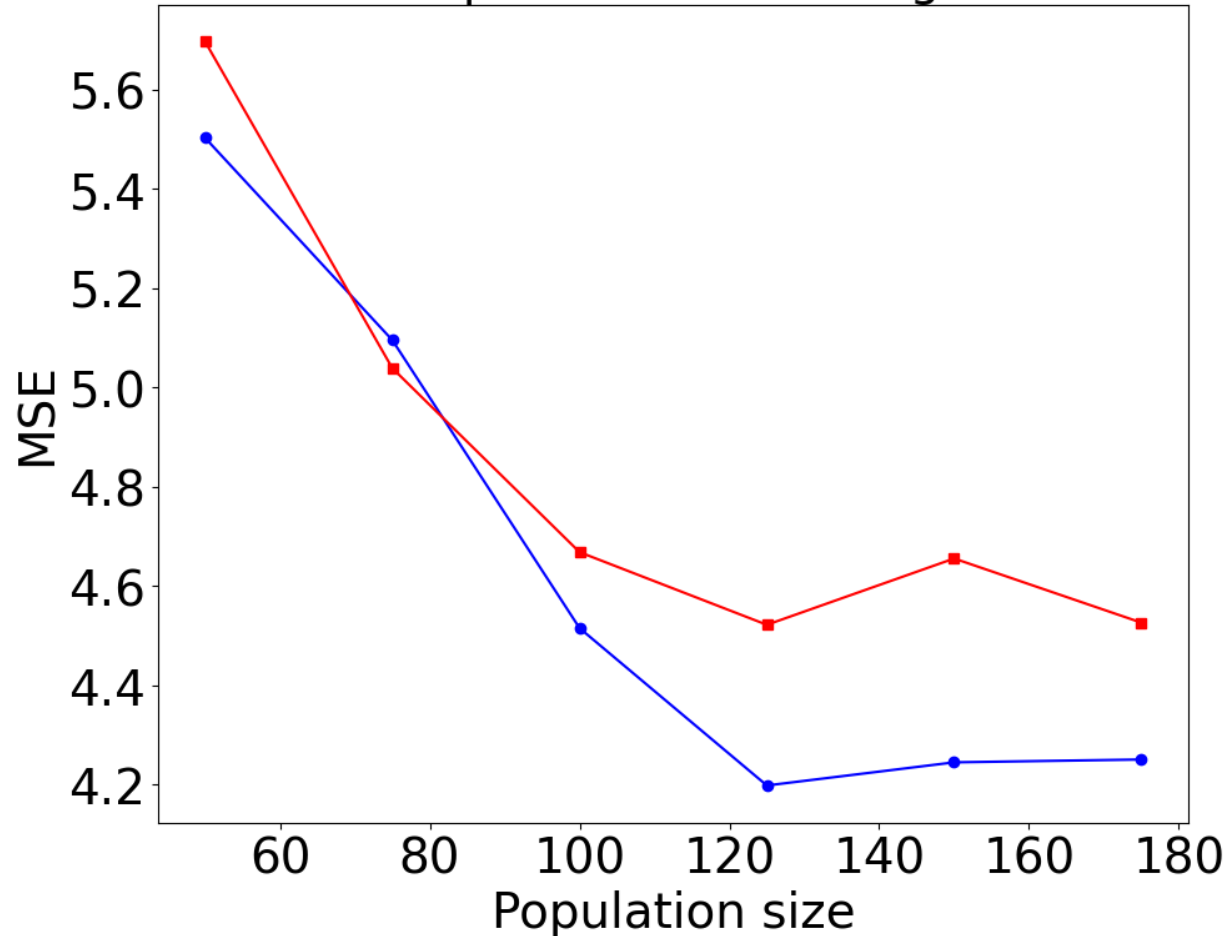


GA Parameter Tuning

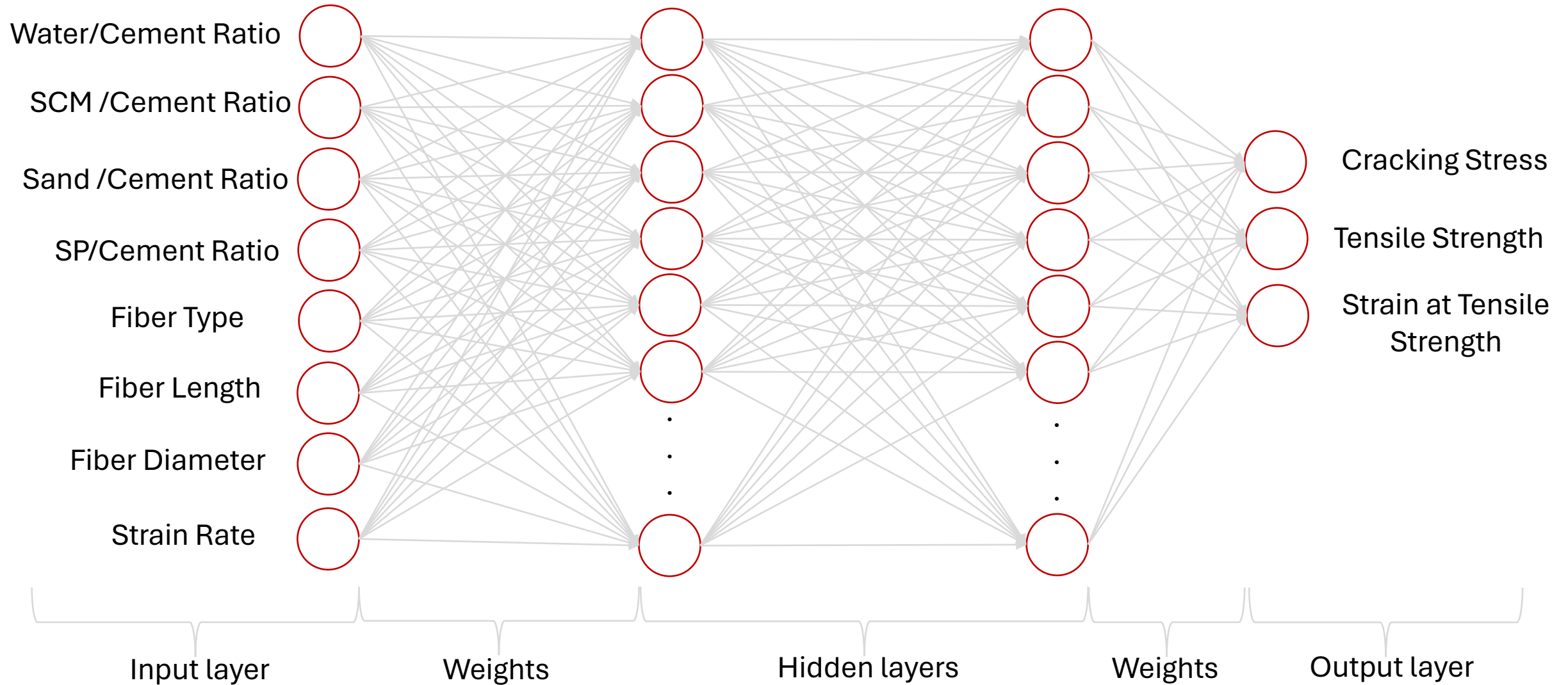
Number of generations tuning



Population size tuning



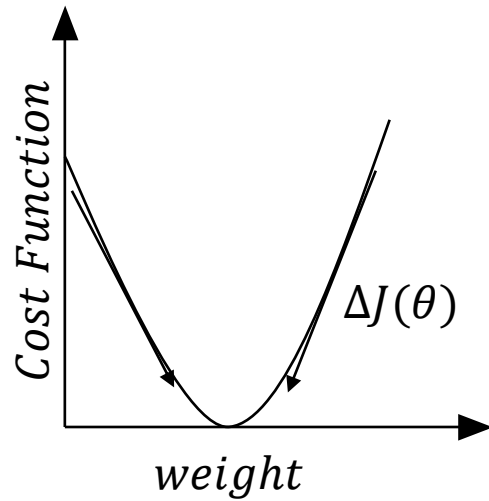
Artificial Neural Network



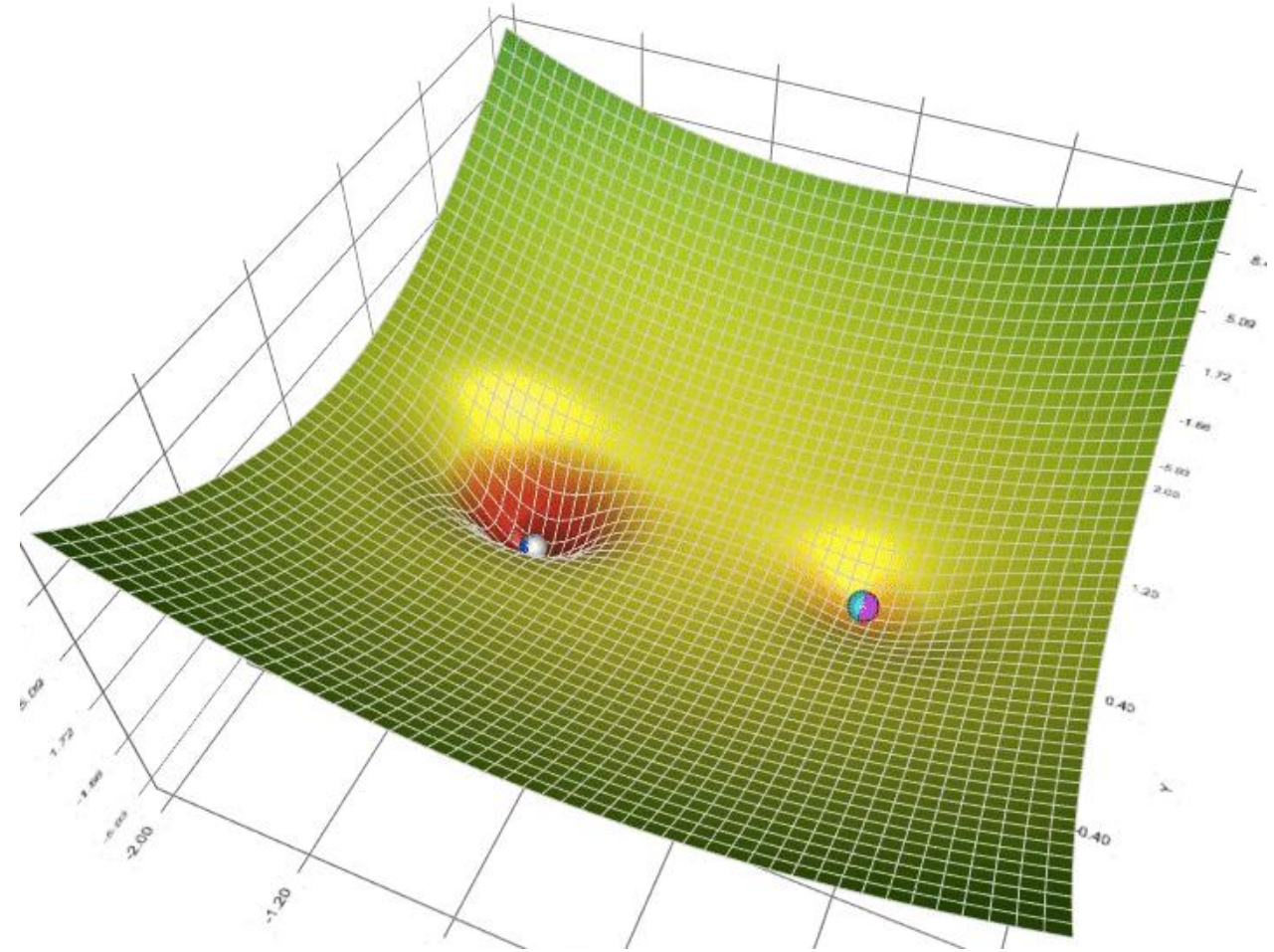
Gradient Descent

$$\text{Cost Function} = \frac{1}{2n} \sum_1^n (y - y^i)^2$$

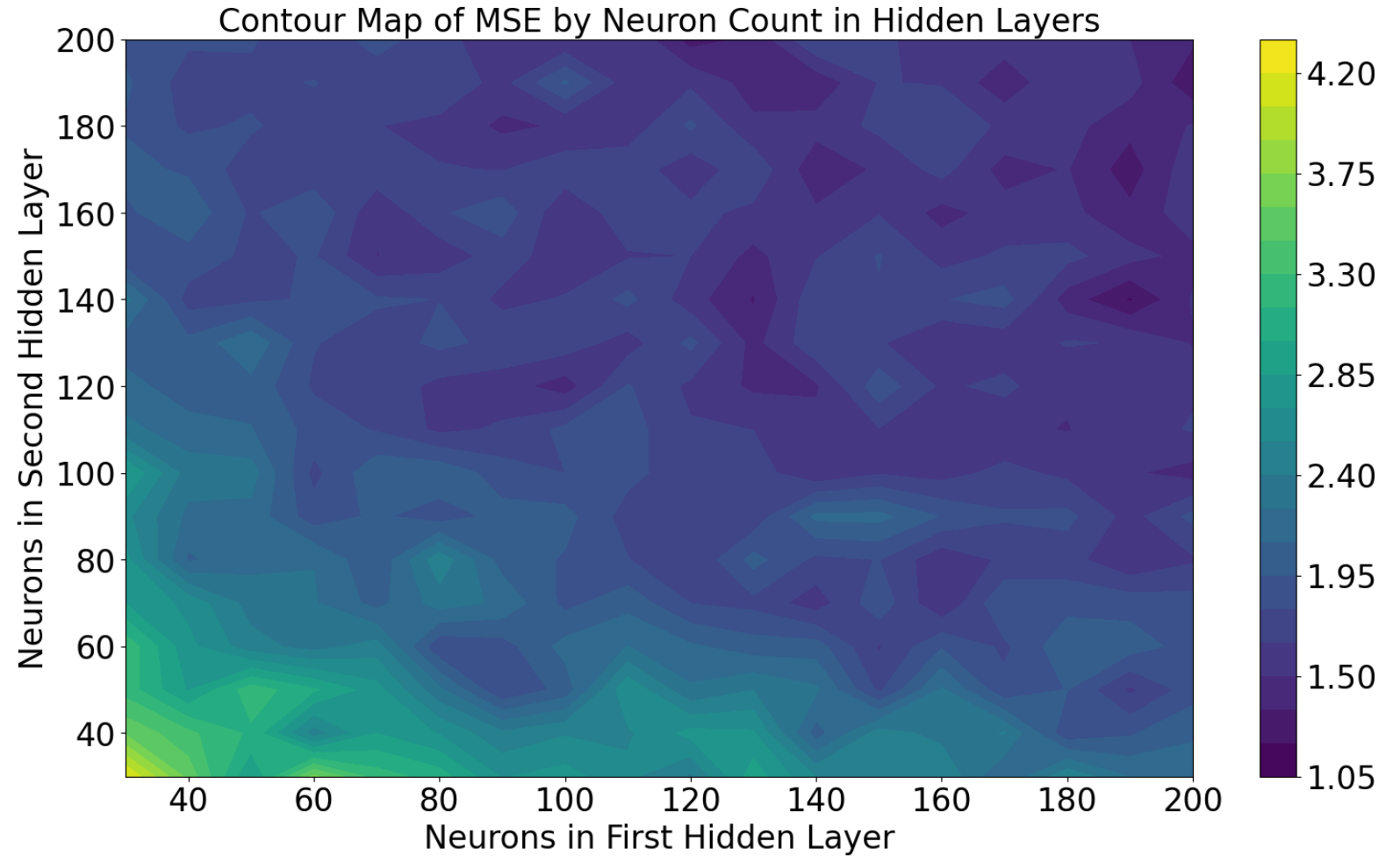
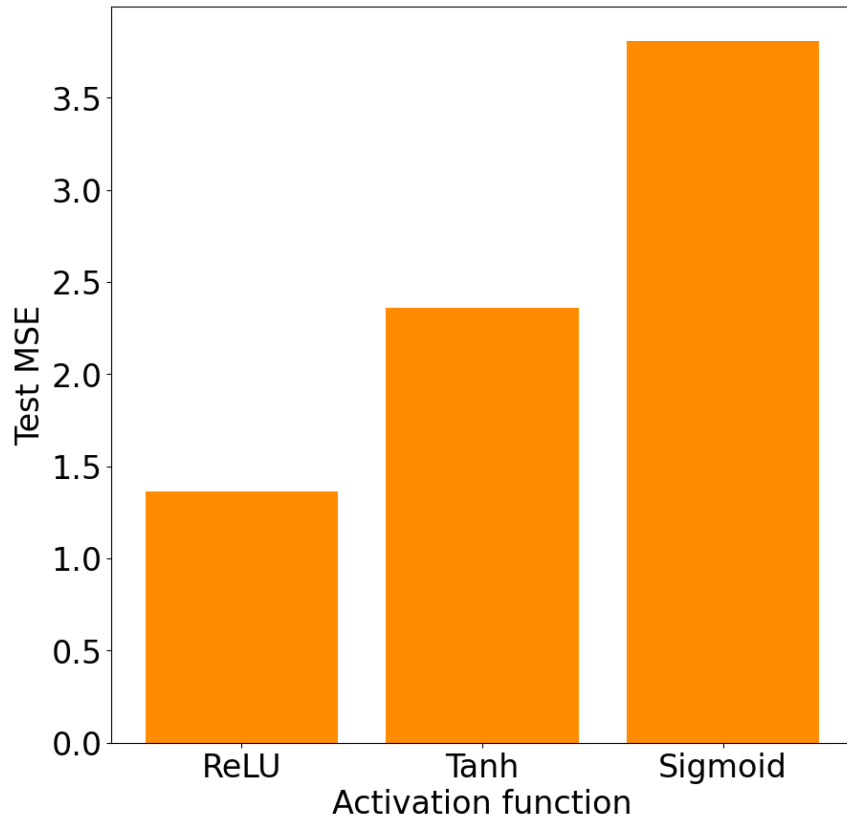
Goal: Minimize cost function



$$\theta_n = \theta_n - J(\theta_n)$$

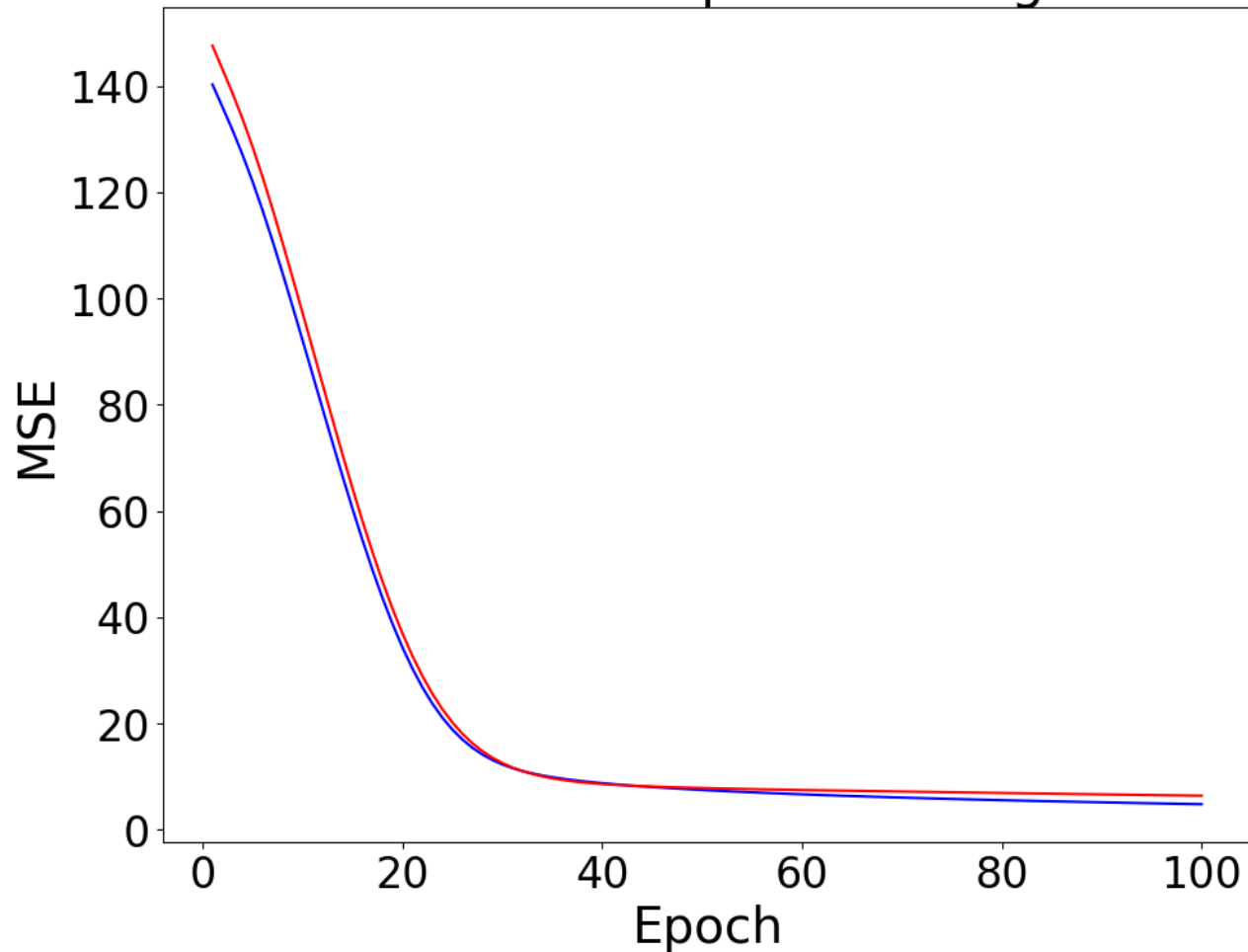


ANN Parameter Tuning



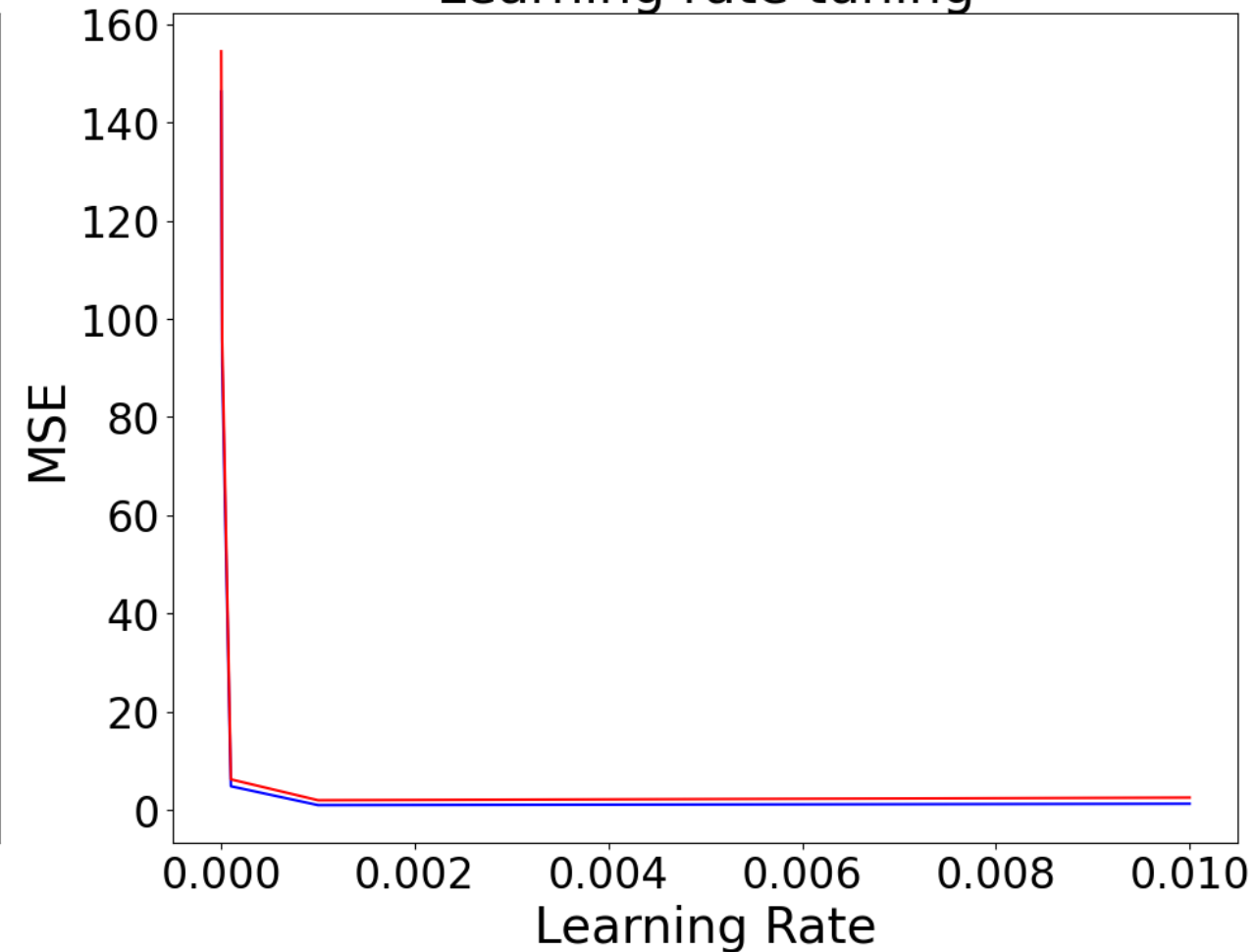
ANN Parameter Tuning

Number of epochs tuning



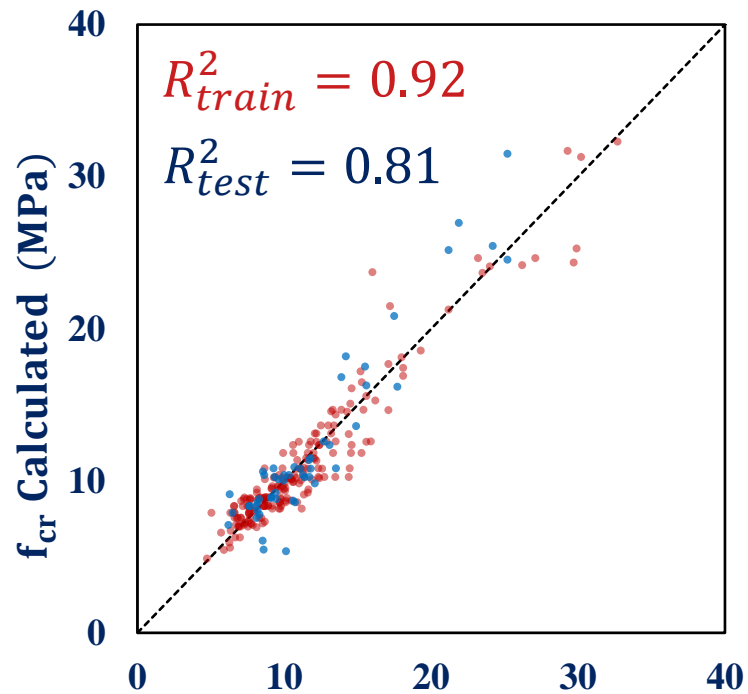
— Training MSE — Testing MSE

Learning rate tuning

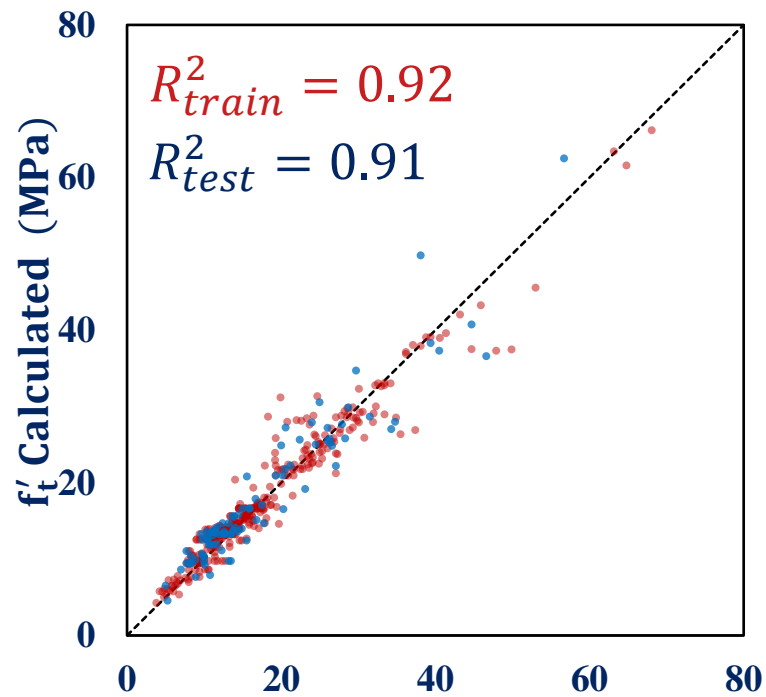


— Training MSE — Testing MSE

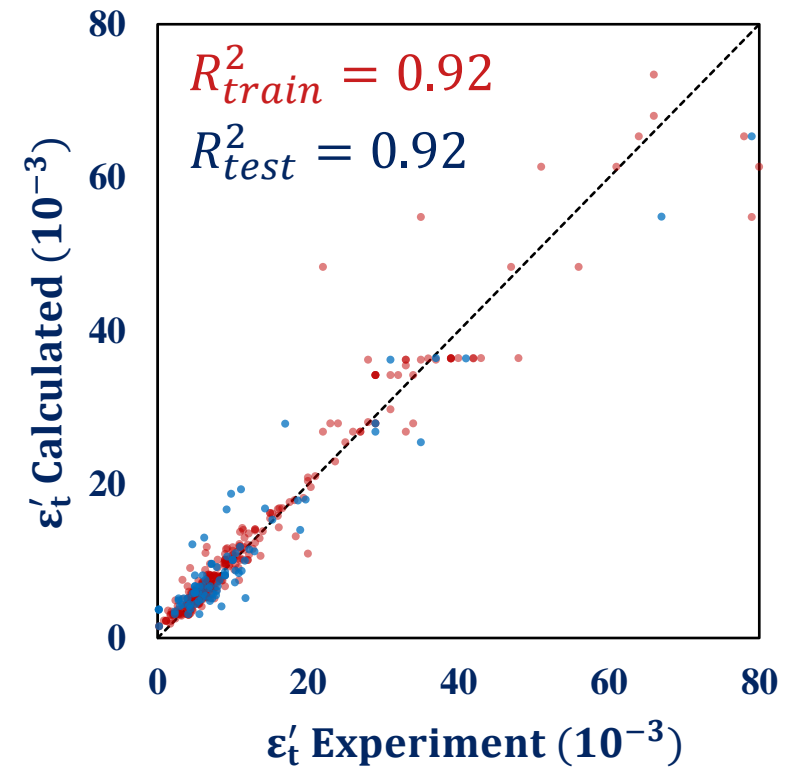
ANN Results



• Train data • Test data



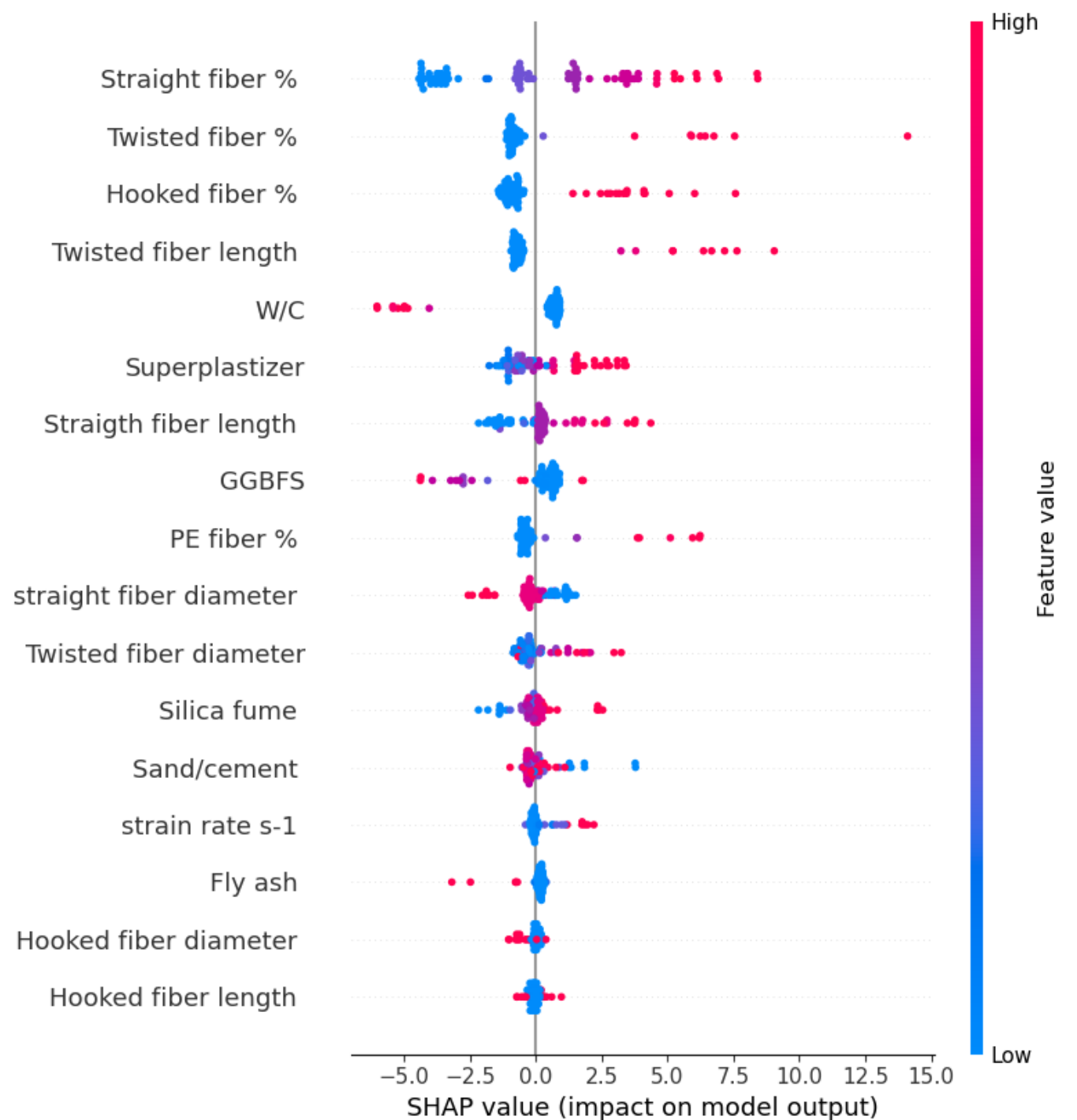
• Train data • Test data



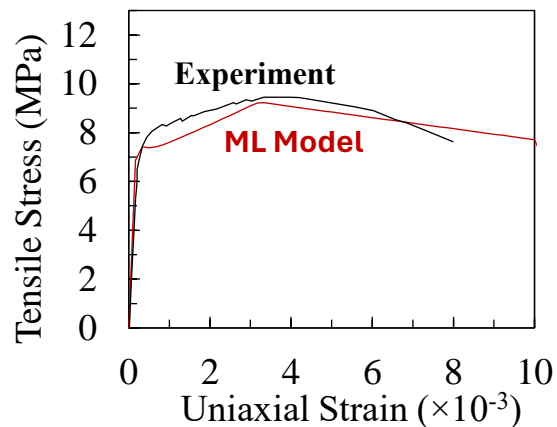
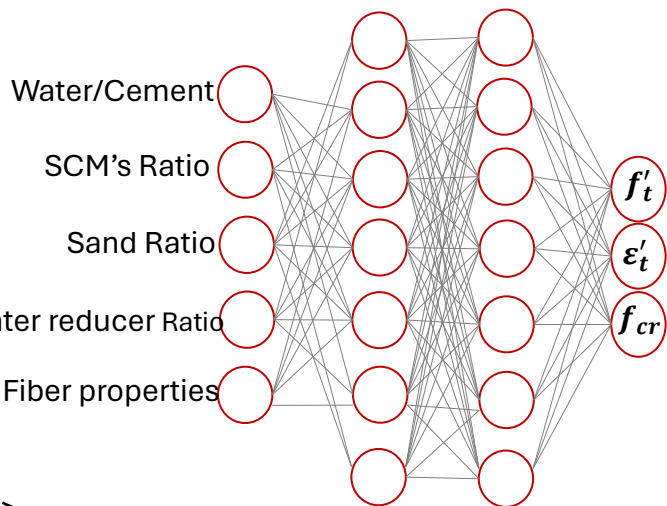
• Train data • Test data

SHAP

- SHapley Additive exPlanations (SHAP) helps explain the output of any machine learning model.
- SHAP makes complex models more understandable by quantifying the influence of each input feature on the output.
- By understanding how a model makes its decisions, developers can identify and mitigate biases within the model.
- SHAP is generally useful to interpret the results of ANN algorithms which are generally acting as “black boxes”

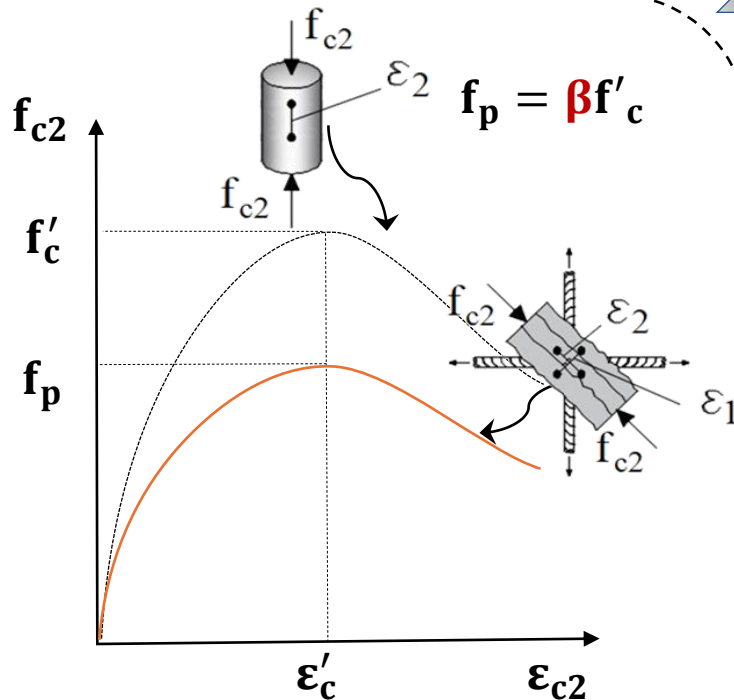
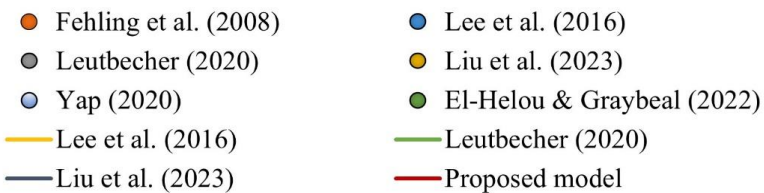
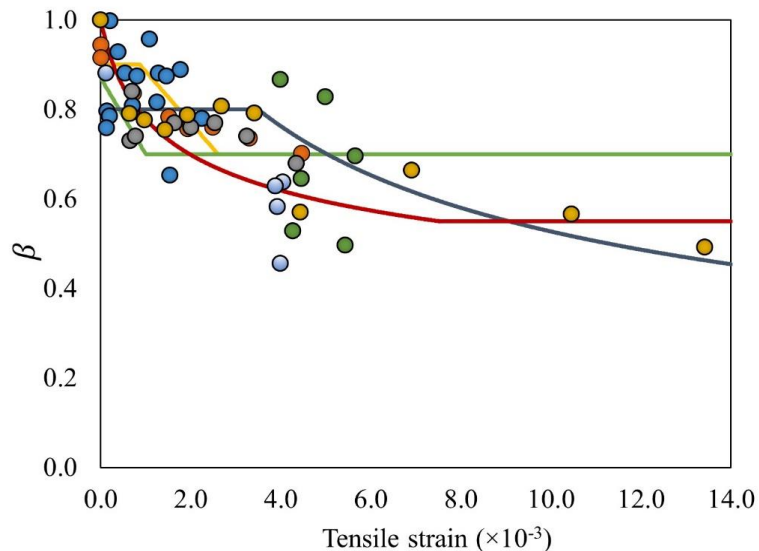
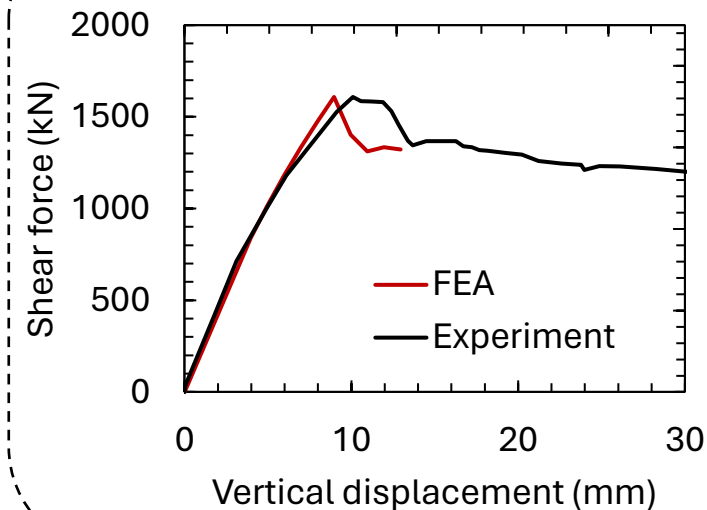


Tension Response



Modelling approach

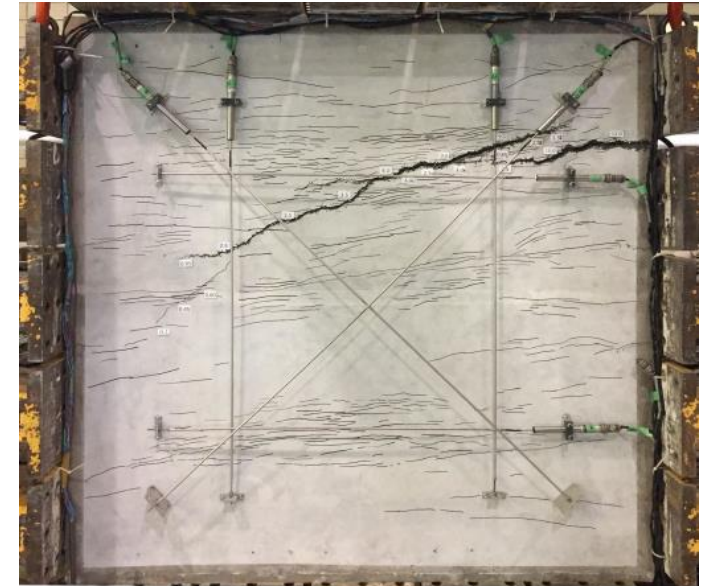
FEA versus Experiment



Model validation – UHPC panels

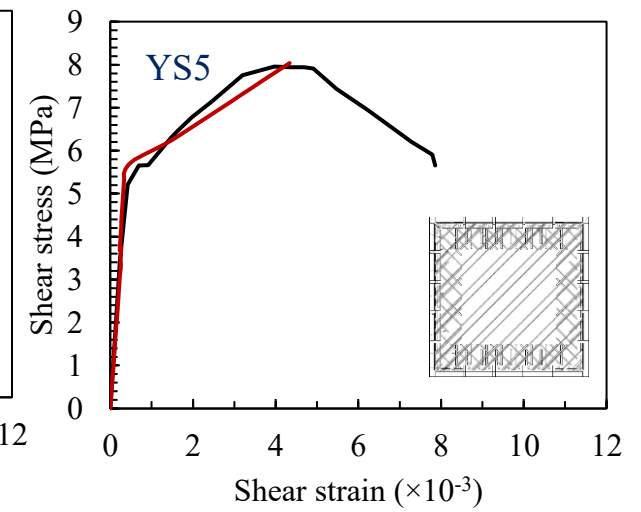
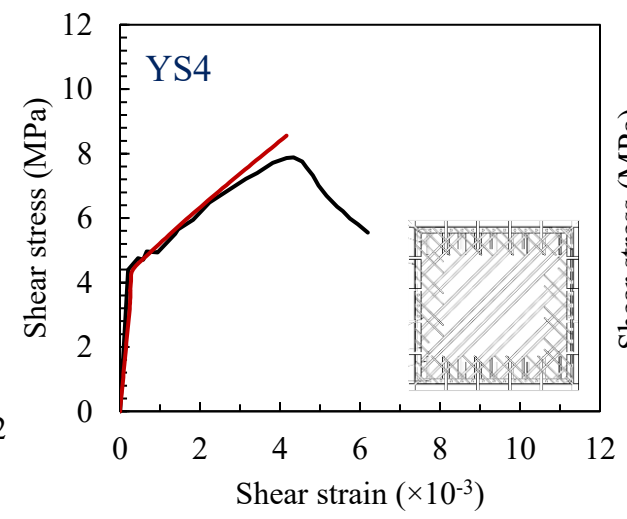
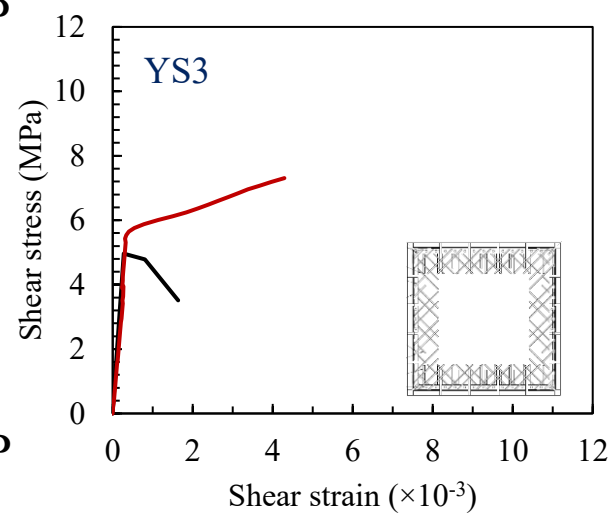
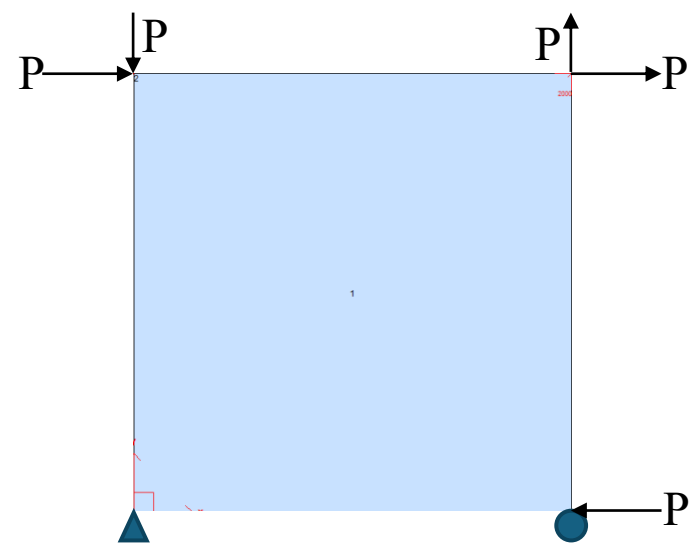
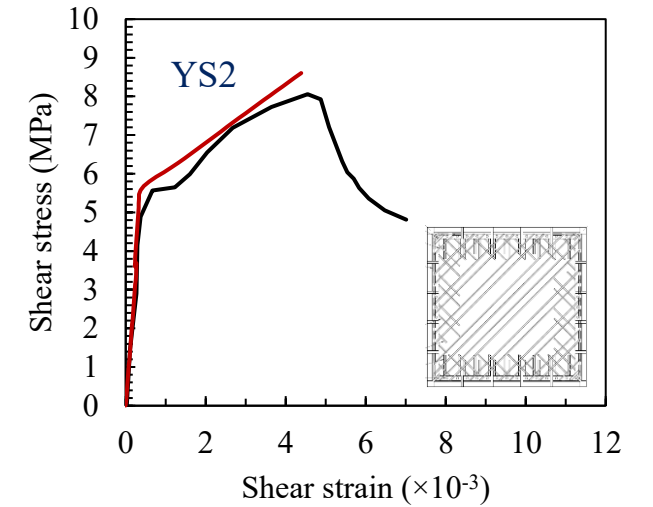
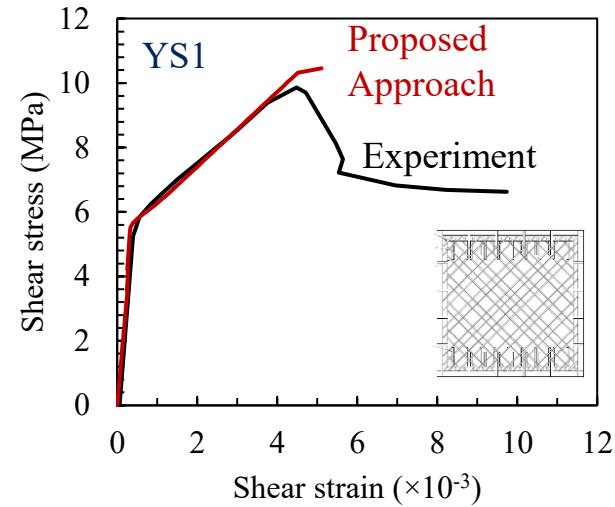
UHPC panel specimens tested at the University of Toronto - subjected to pure shear

Specimen	f'_c (MPa)	Thickness (mm)	ρ_x (%)	ρ_y (%)
YS1	171.5	215	0.86	0.86
YS2	167.5	206	0.90	0.00
YS3	164.2	212	0.00	0.00
YS4	157.0	217	2.56	0.00
YS5	160.3	224	0.43	0.00



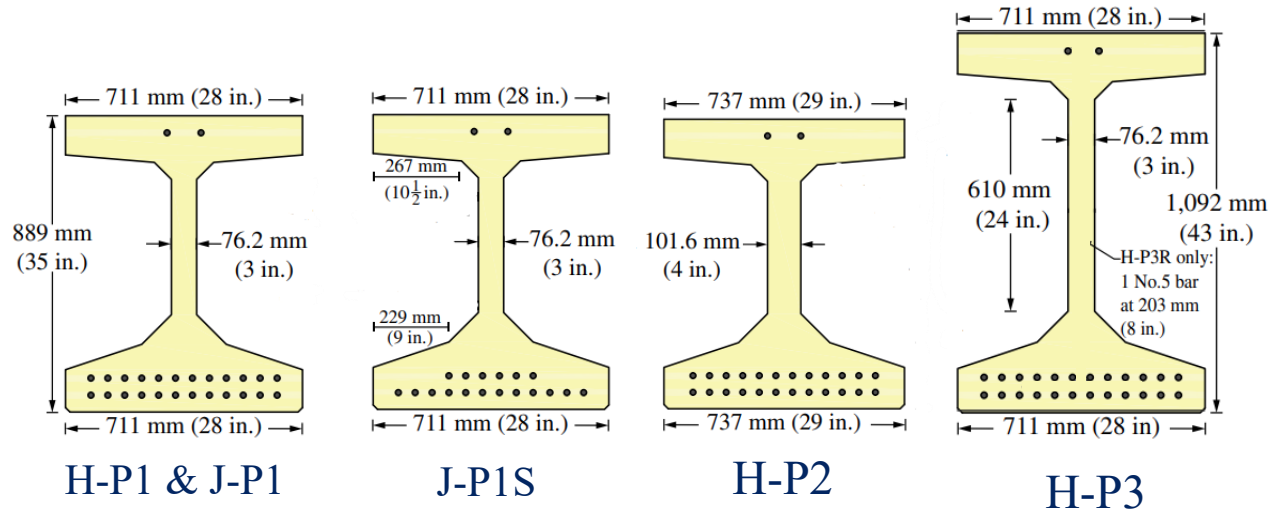
YAP 2020 PANEL SPECIMENS

Specimen	f'_c (MPa)	Thickness (mm)	ρ_x (%)	ρ_y (%)
YS1	171.5	215	0.86	0.86
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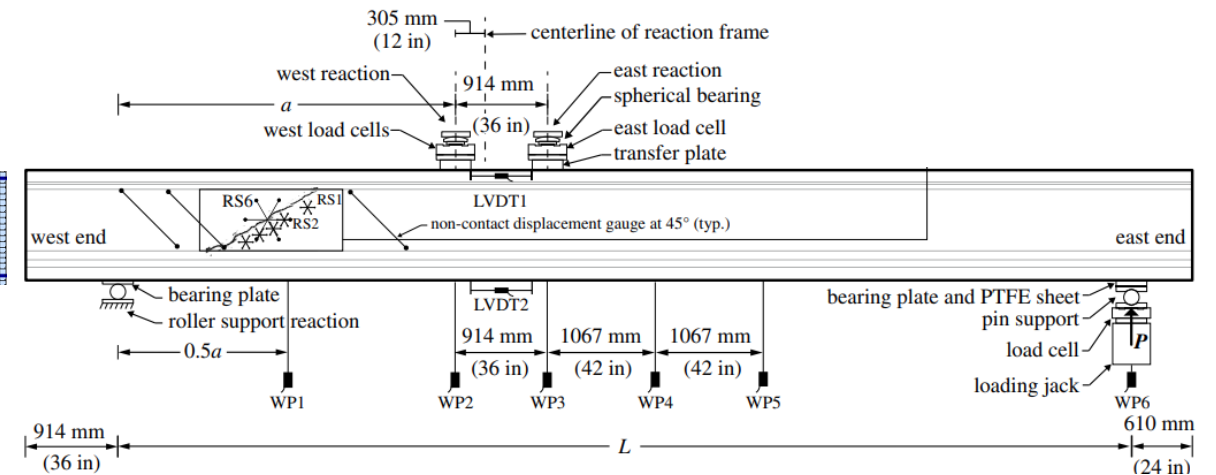
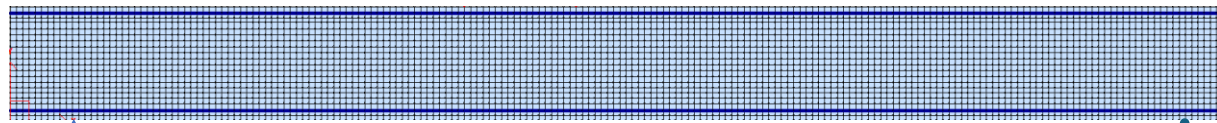




EL-HELOU AND GRAYBEAL 2022 BEAMS



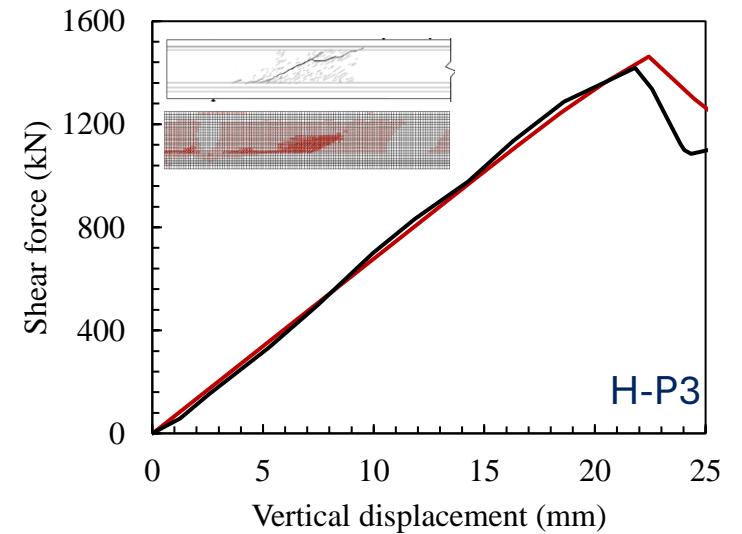
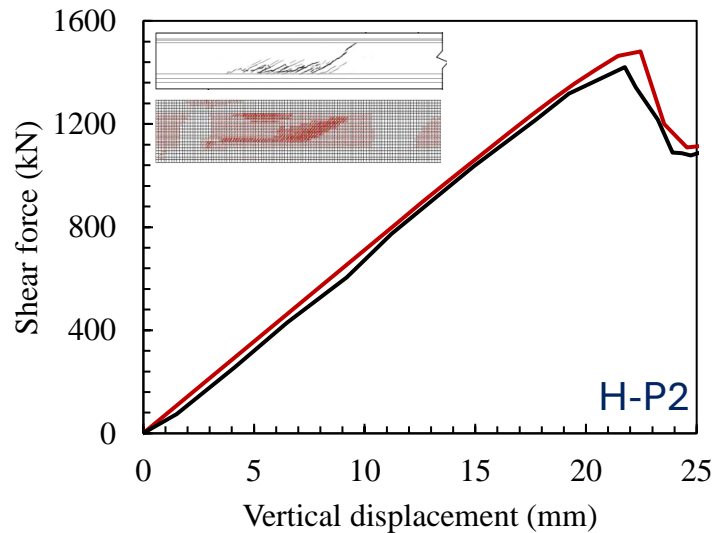
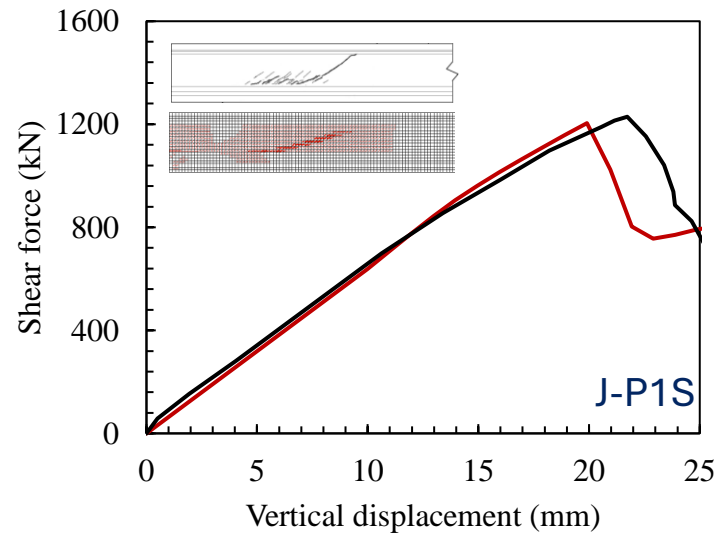
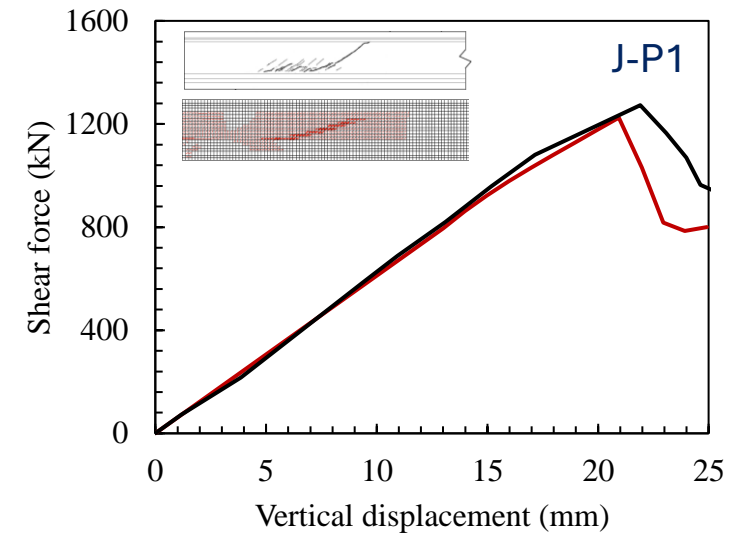
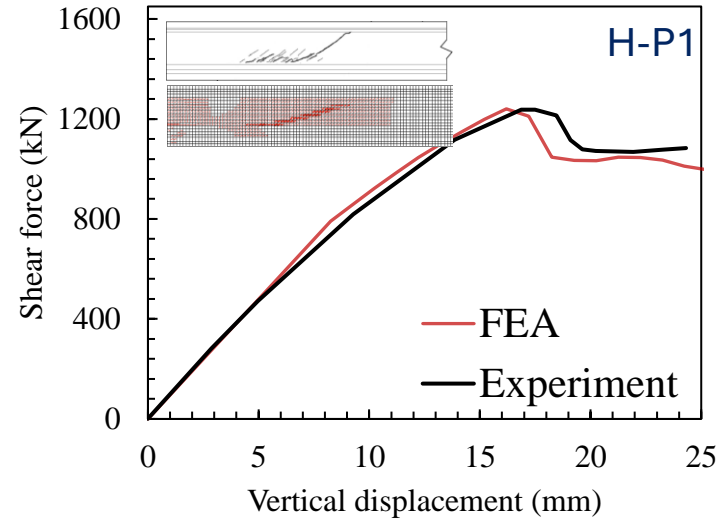
ID	f'_c (MPa)	f'_t (MPa)	A_{pbot} (mm ²)	a/d
H-P1	137	11.3	4552.8	3.5
J-P1	158	8.6	4552.8	3.5
J-P1S	152	9.3	3414.6	3.5
H-P2	140	10.7	4552.8	3.5
H-P3	160	11.5	4552.8	3.5





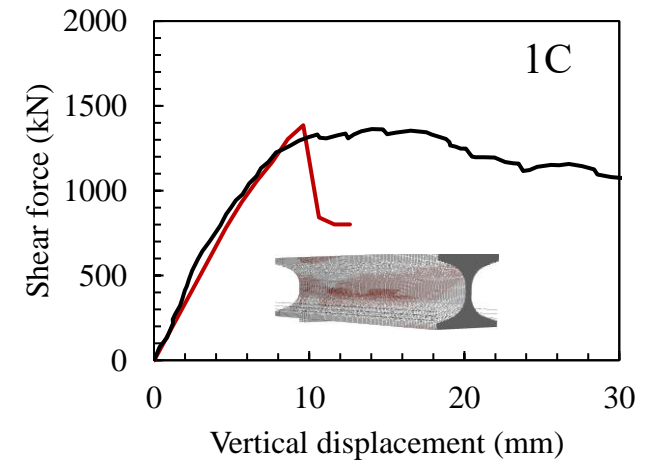
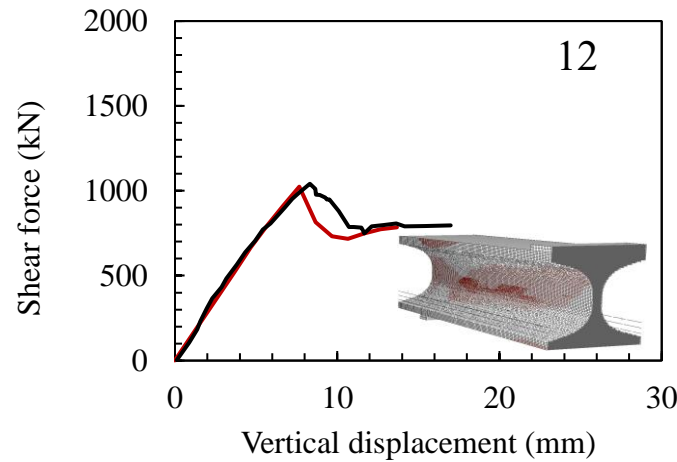
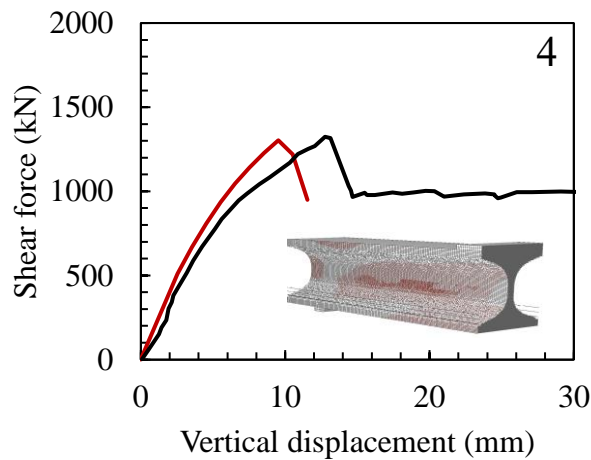
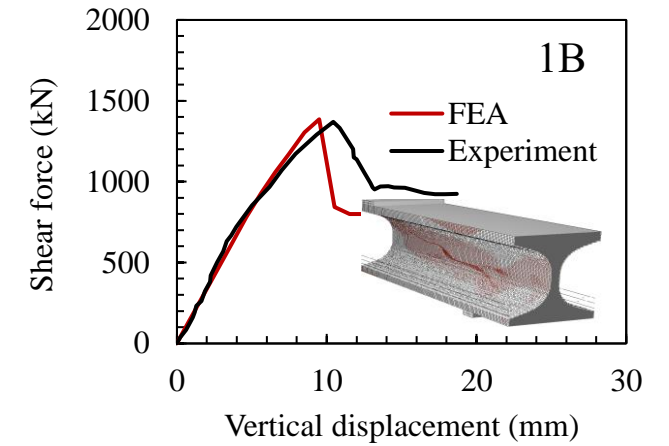
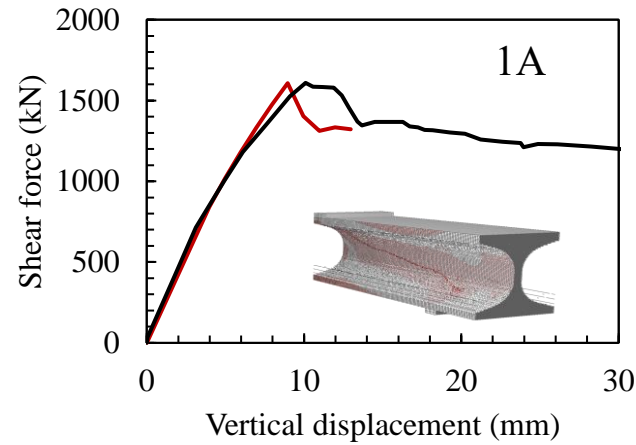
EL-HELOU AND GRAYBEAL 2022 BEAMS

ID	f'_c (MPa)	f'_t (MPa)	A_{pbot} (mm ²)	a/d
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H-P3	160	11.5	4552.8	3.5



PCI 2021 BEAMS

ID	f'_c (MPa)	f'_t (MPa)	A_p (mm ²)	b_w (mm)	a/d
1A	155	15.8	4592	75	2.5
1B	120	11.8	4592	75	2.5
1C	120	11.8	4592	75	2.5
4	118	11.8	2296	75	2.5
12	125	11.8	4592	50	2.5



Conclusions & Future work

Conclusions:

- The ANN-based model developed for predicting the tension response of UHPC proved to be reasonably accurate for the set of specimens analyzed.
- It is feasible to employ an ANN-based tension response model of UHPC within a NLFEA framework.
- The direct tension database is available in the QR code attached.

Future work:

- Developing a Bayesian neural network to provide a probabilistic estimation of the tension characteristics of UHPC composites.
- Using the developed formulation to analyze the response of retrofitted UHPC bridge piers with UHPC jacketing.
- Analyzing the response of UHPC shear walls.



Thank You!

