Parametric model validation using PINNs+GCNs

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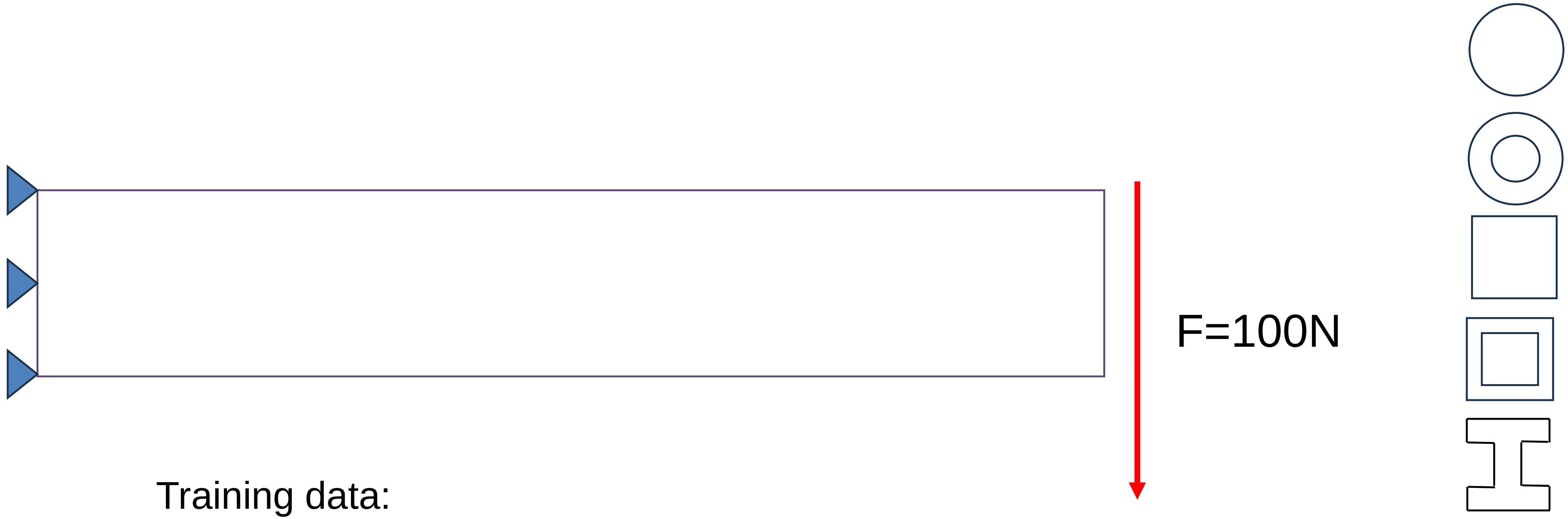
Overview

- An AI surrogate model was developed to solve a simple structural statics problem using Physics-Informed Neural Networks (PINNs).
- **The architecture of the AI model was based on Graph Convolutional Networks (GCNs), which utilize the geometry of the mesh model as input data. This approach was adopted with the aim of creating surrogate models capable of handling complex part geometries that cannot be represented by simple parameters.**
- Parameters that define the beam shape, such as height and width, were not directly used as input data. Instead, they were utilized solely to create the mesh model.
- The loss function incorporated both physical equations and reference data. This inclusion allows for the training process to be guided by both theoretical principles and empirical data.
- An AI model capable of predicting displacement and stress was developed, and its performance was evaluated. The results indicated excellent predictive accuracy, demonstrating the model's potential effectiveness for structural analysis applications.

Training Models

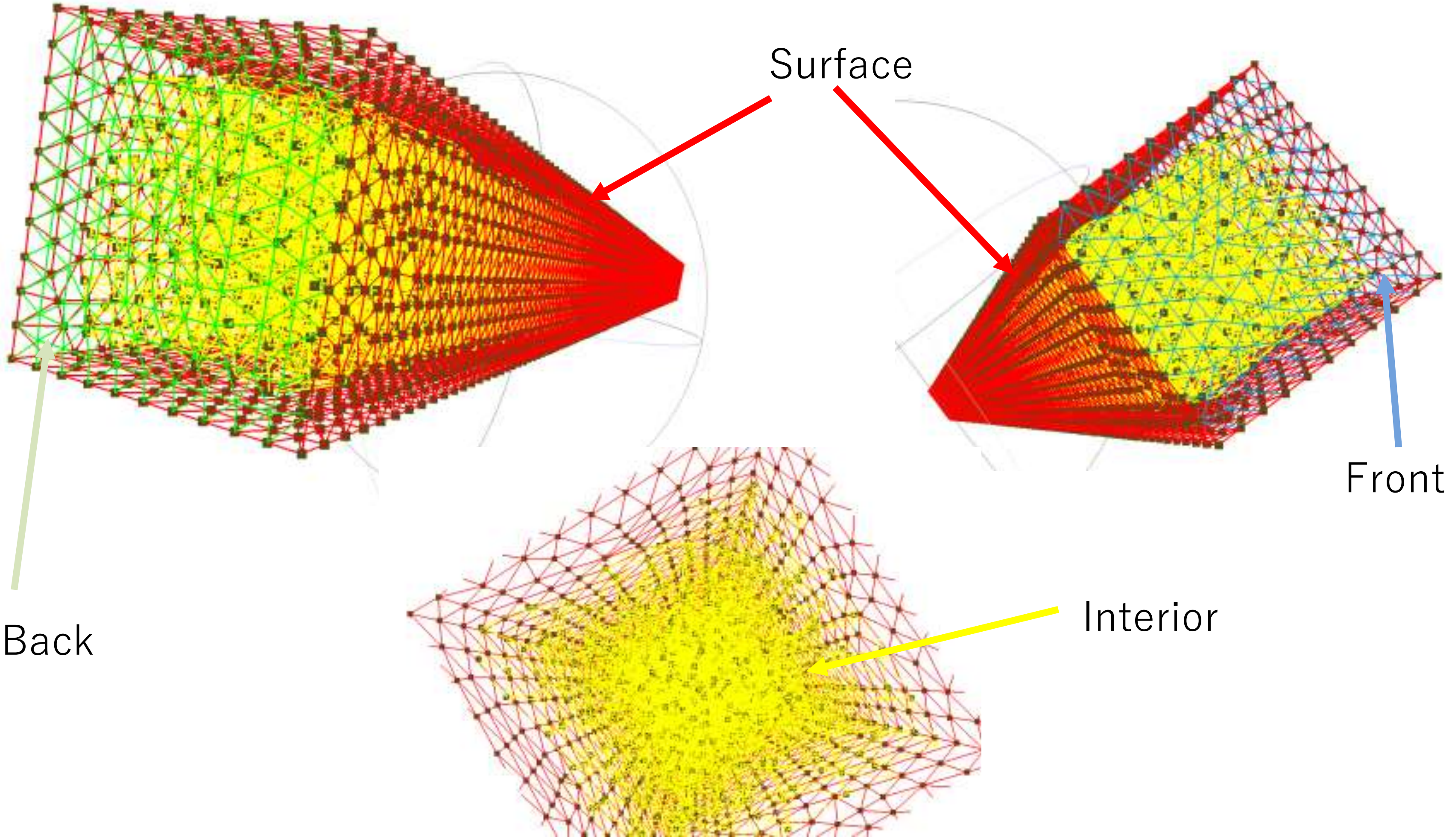
- The structural analysis model employed for training is a cantilever beam bending model, characterized as a linear static analysis model. The model parameters include length, width, and height, with fixed constraints, applied loads, and material constants.(Page 4)
- A total of 325 input mesh shapes were prepared as reference data from FEM analysis, consisting of 65 samples for each of five distinct cross-sectional shapes. The mesh size was held constant across all samples.
- FEM analyses were conducted on these mesh shapes, and the results were used as reference data to support the AI model's training process.
- Data references were collected for all nodes within the model. Nodal data were classified into four categories: interior nodes, surface nodes, back nodes (constraint points), and front nodes (load points).(Page 5)

Target cantilever beam model (5 types of cross-sectional shapes)



Training data:
65 data for each of the 5 cross sections
Total 325 data

Mesh nodes 4 groups:
front, back, surface, and interior



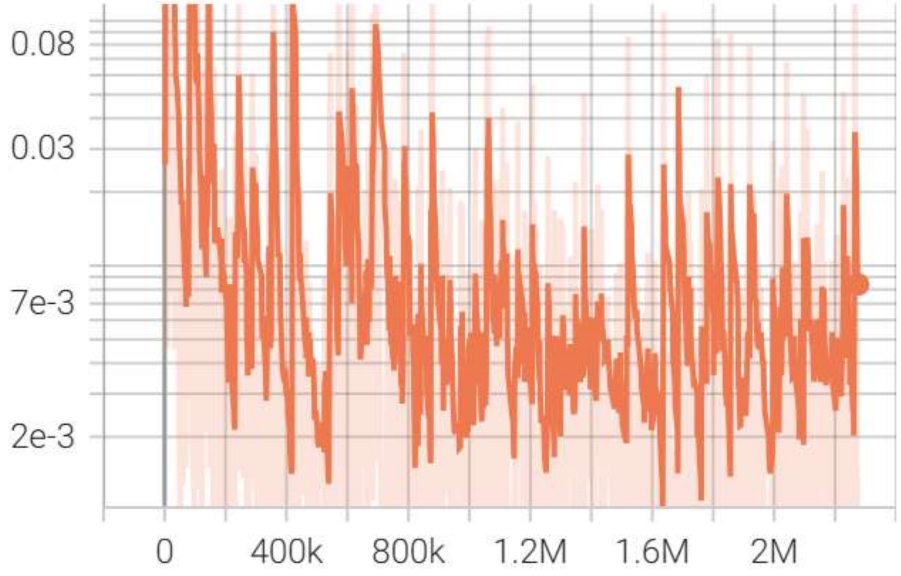
Displacement prediction AI model

Training result

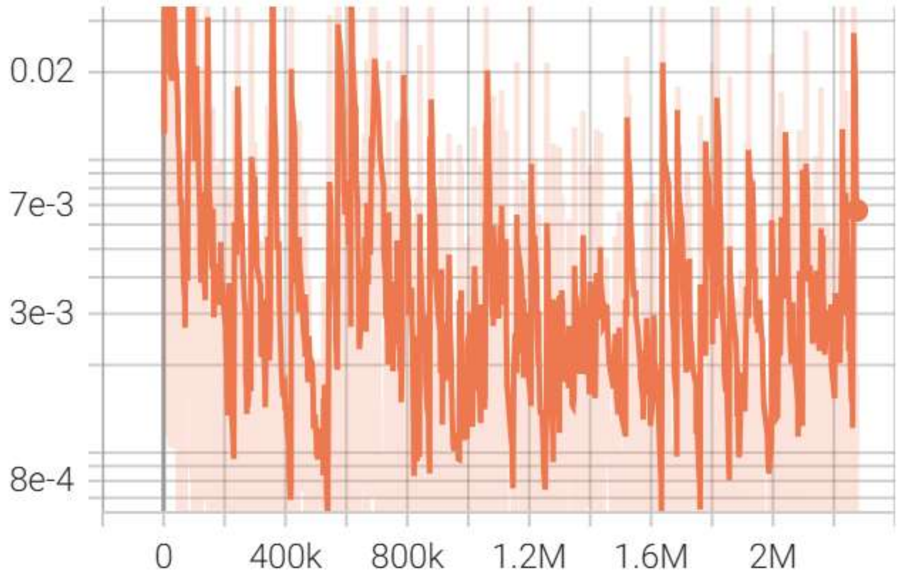
- The evolution of the loss function during training is illustrated in the graphs depicting overall loss (Train loss), X displacement (u), and Z displacement (w).The overall loss, averaged for each epoch of the plot(*), is also displayed in the lower right corner (page 9).
- The x-axis of the graph represents the number of iterations; the graph appears to oscillate when all iteration values are utilized, while the graph averaged for each epoch (bottom right) converges smoothly.
- The R^2 values for X and Z displacements were 1.0 (page 10).

*1 epoch = 325 iterations

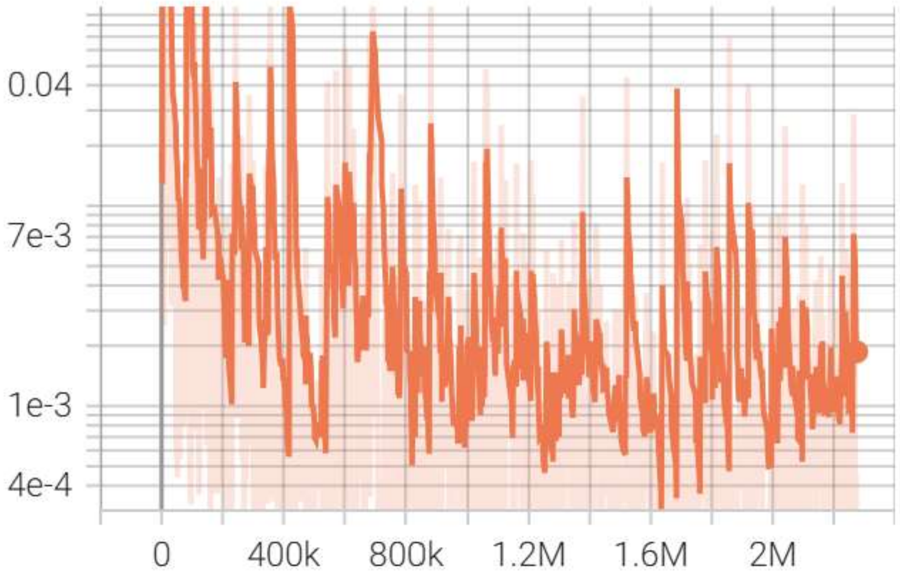
train_loss
tag: train_loss



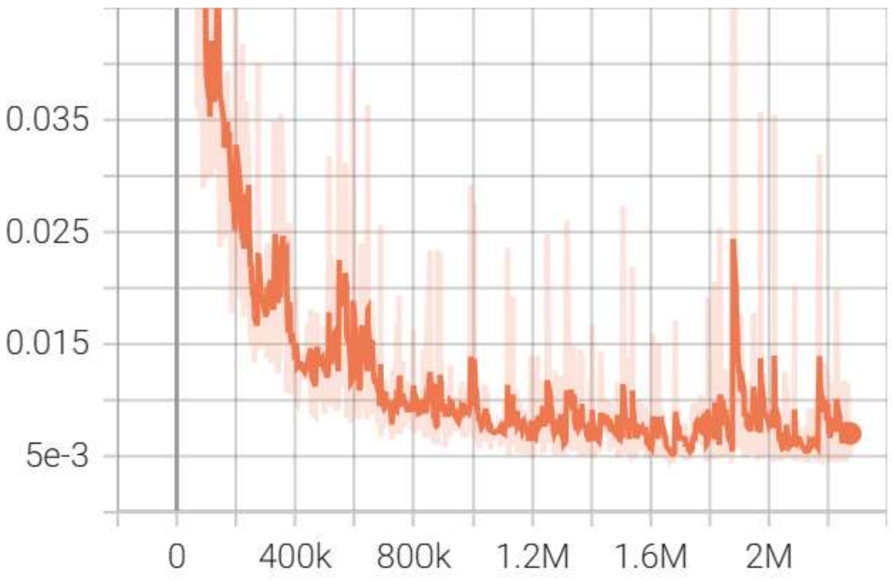
u
tag: u



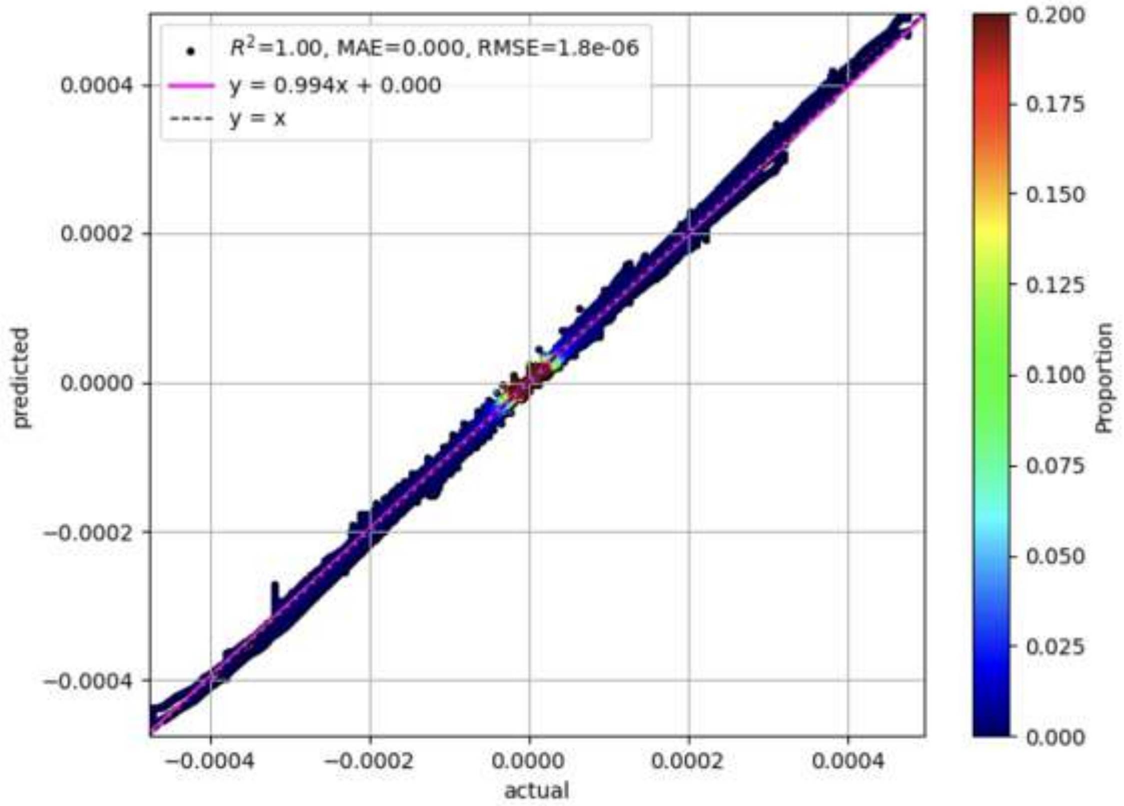
w
tag: w



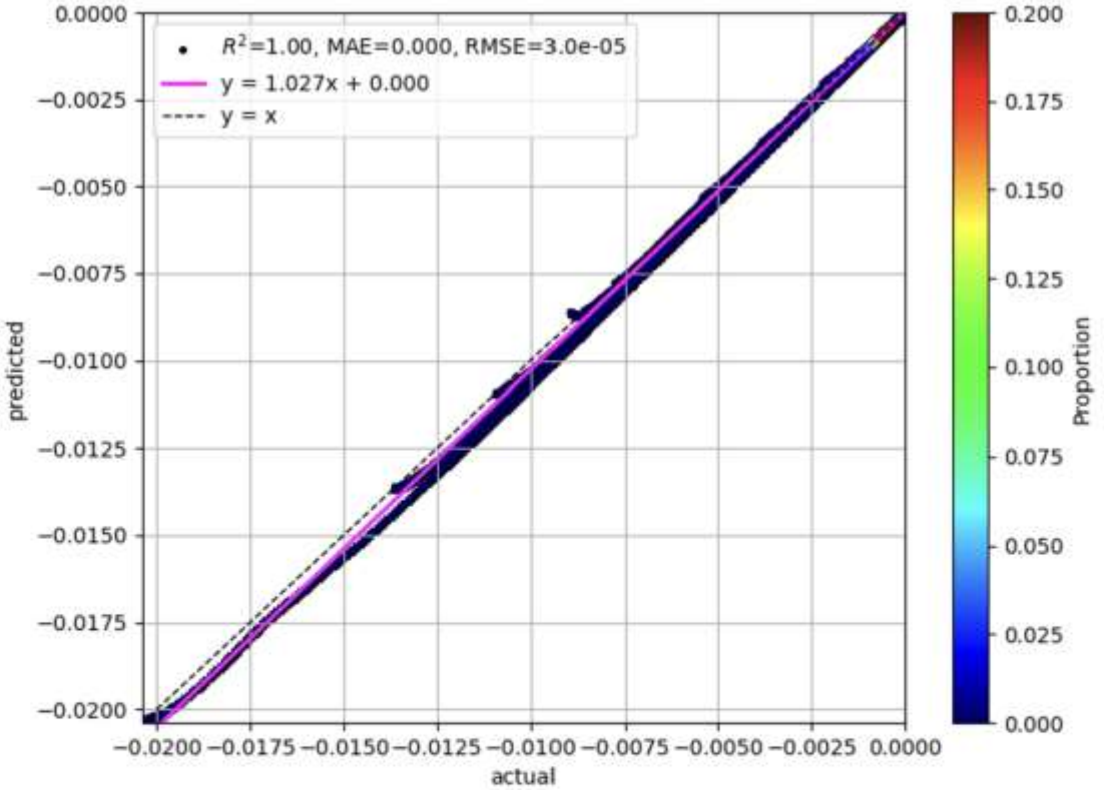
epoch_train_loss
tag: epoch_train_loss



Displacement X



Displacement Z



Displacement prediction results (Known model)

- The trained surrogate model is employed to validate the prediction results in the known model, which corresponds to the shape dimensions used for training.
- The prediction results are compared across the five geometries presented in the table below. There is excellent agreement with the FEM results (Actual: reference value) for W (displacement in the Z direction) at the right end (free end).
- Detailed results, including displacement contour plots in the x-direction, displacement contour plots in the z-direction, deformation diagram comparisons, and error distribution contour plots, are provided (see pages 12 and following).

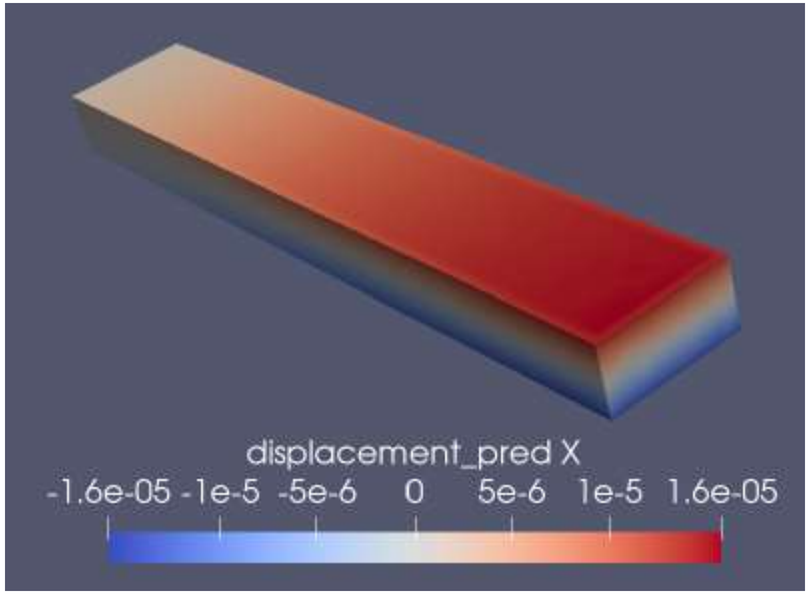
Cross-section	Z disp. (ref. value)	Z disp. (Predicted)	Error	Note
Rectangular	-3.00E-04	-2.90E-04	0.03	Height: 11,Width: 13,Length: 75
Hollow rectangular	-3.00E-04	-2.90E-04	0.03	Height: 10,Width: 15,Thickness: 1.5,Length: 120
Circular	-4.60E-04	-4.70E-04	0.02	Radius: 8,Length: 100
Hollow circular	-5.20E-04	-5.00E-04	0.04	Radius: 7.5,Thickness: 1,Length: 120
I shape	-2.30E-04	-2.20E-04	0.04	Height: 12,w: 12,t1: 3,t2: 1.5,Length: 120

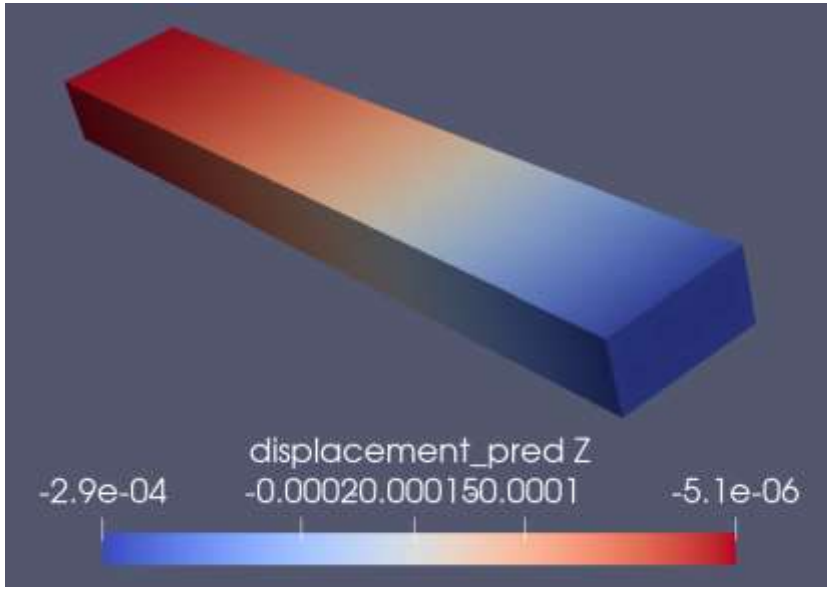
Rectangular section

- Height: 5
- Width: 10
- Length: 60

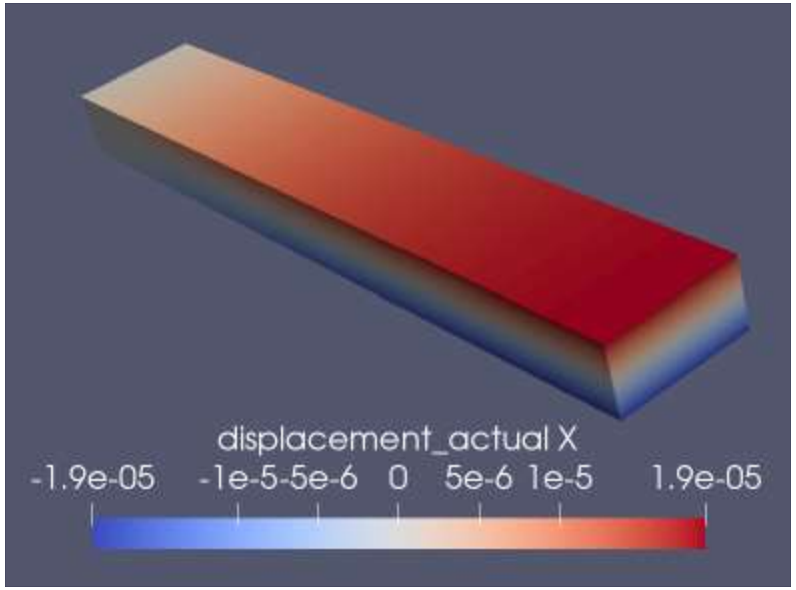
Displacement X | Displacement Z

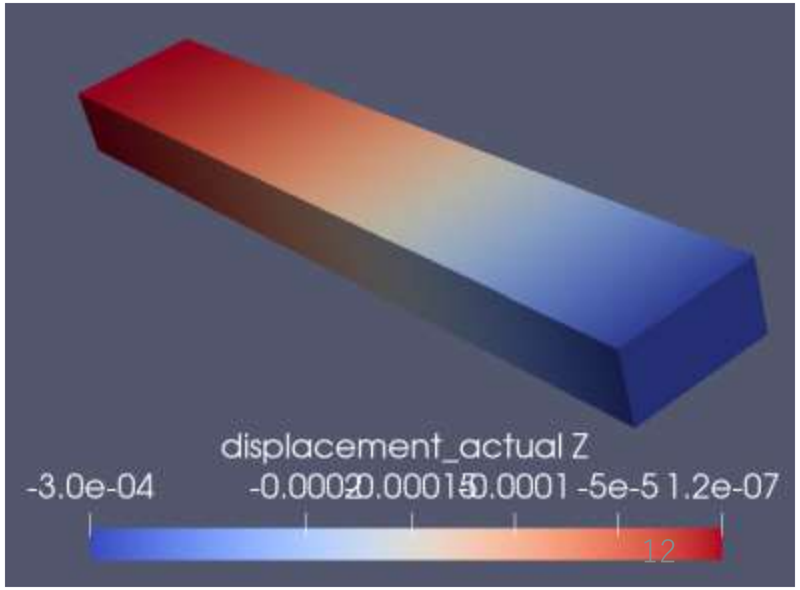
Predict



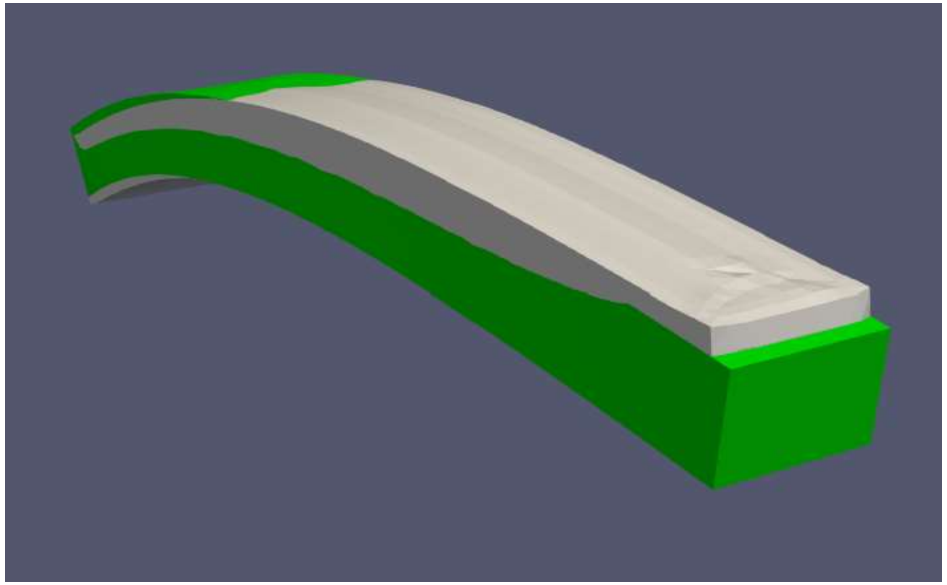


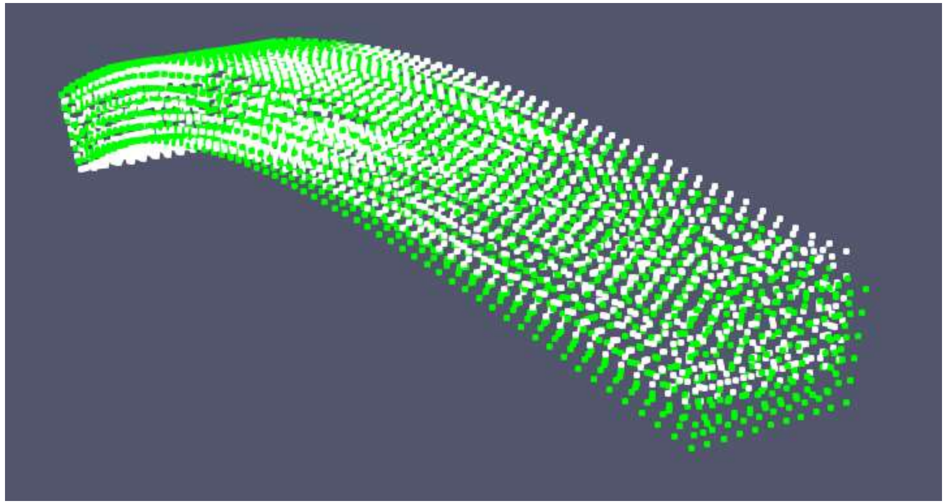
Actual

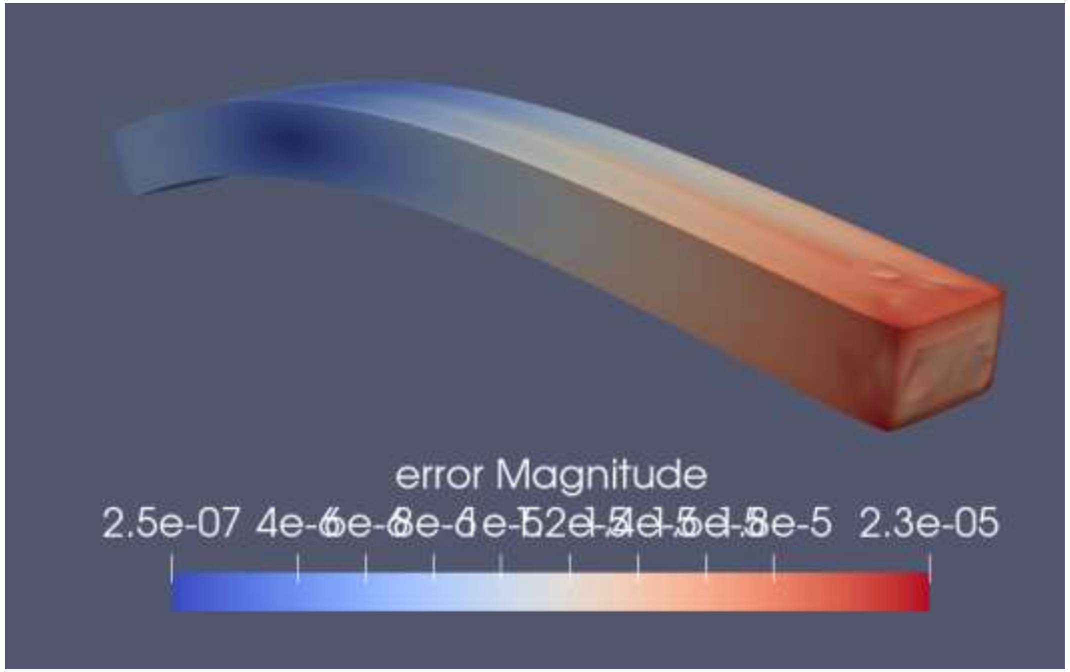




Deformation







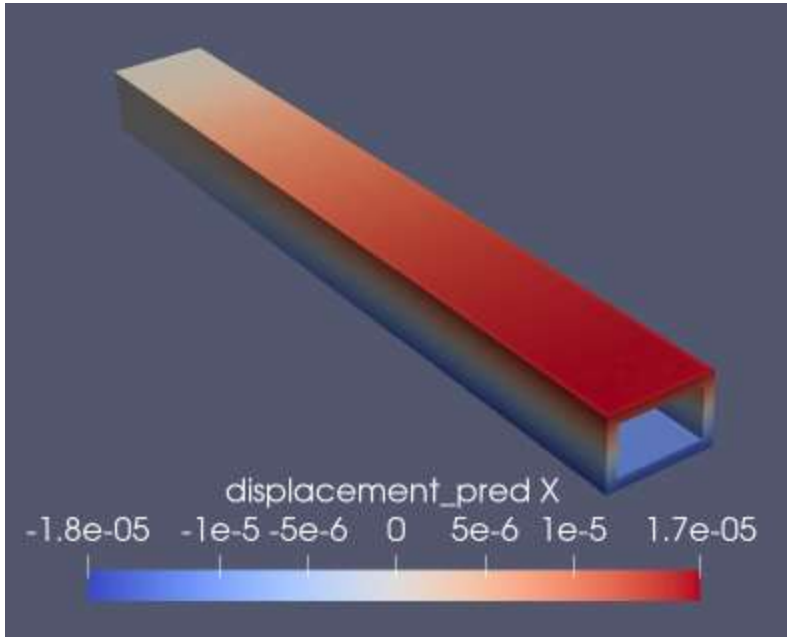
Hollow rectangular section

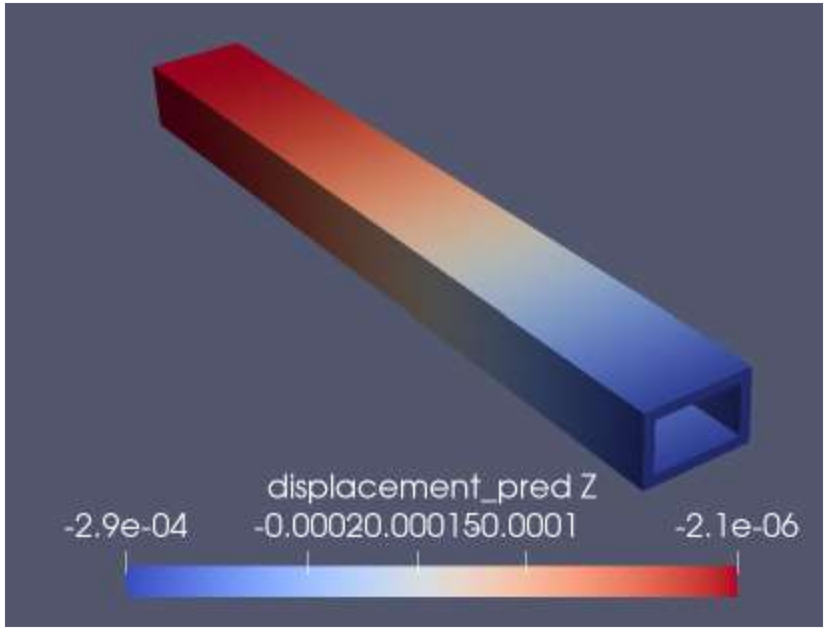
- Height: 10
- Width: 15
- Thickness: 1.5
- Length: 120

Displacement X

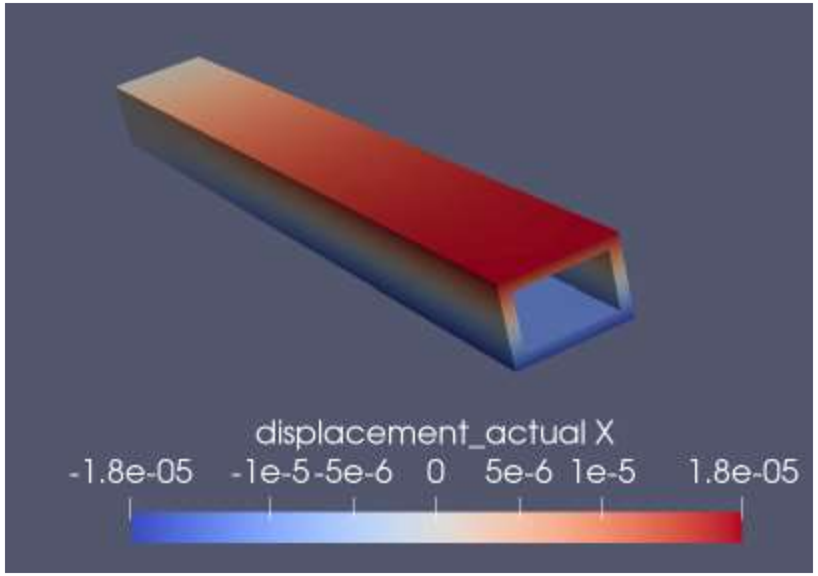
Displacement Z

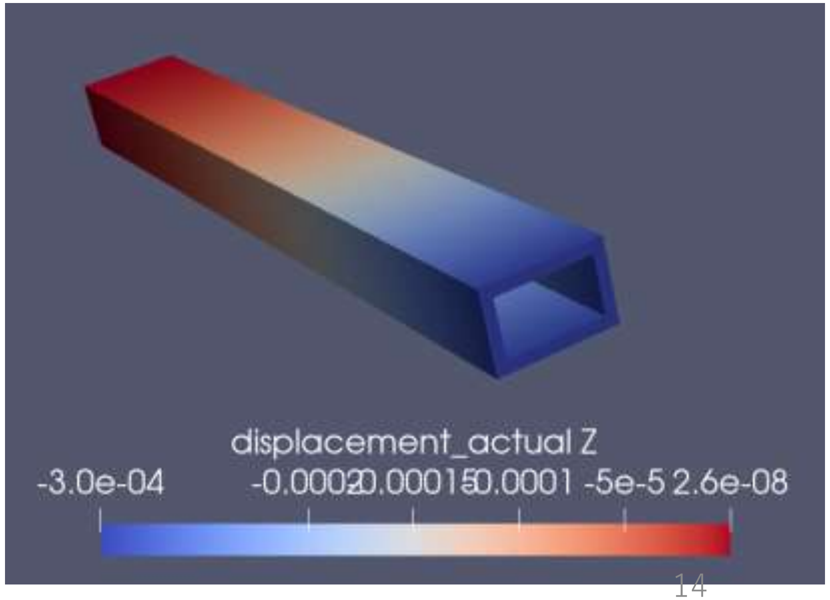
Predict





Actual





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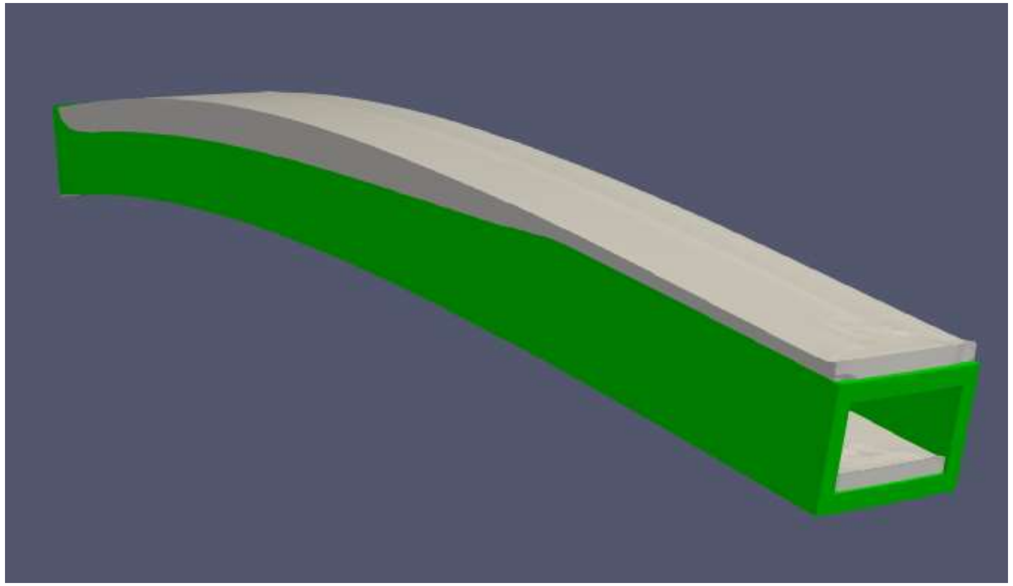
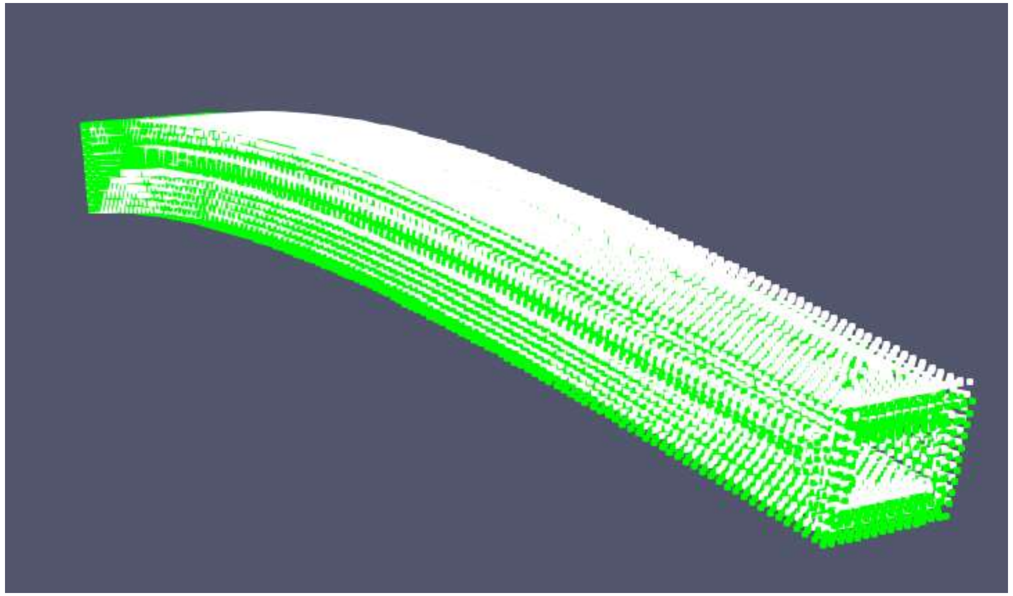
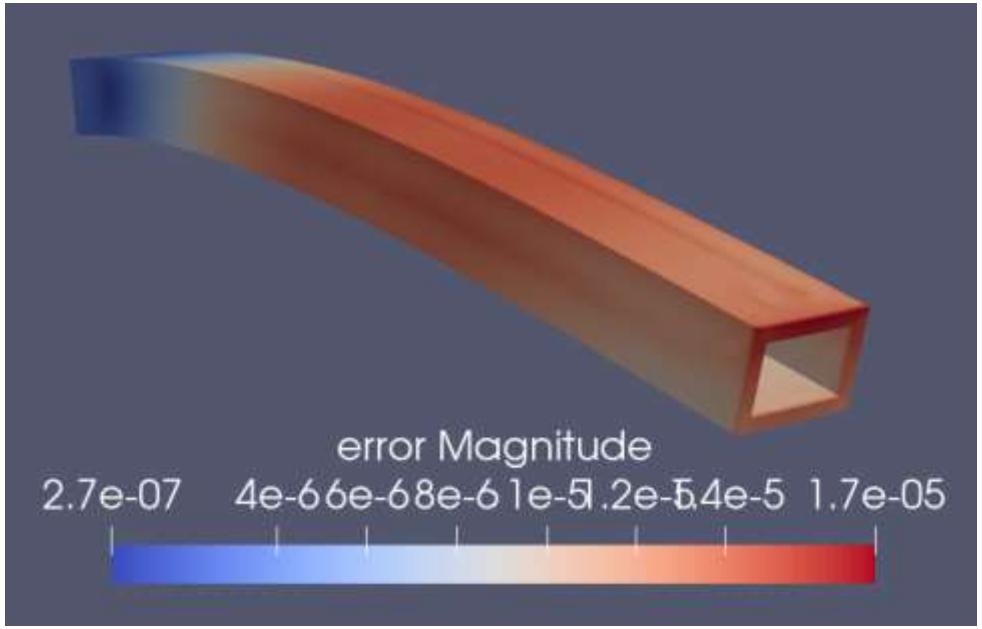




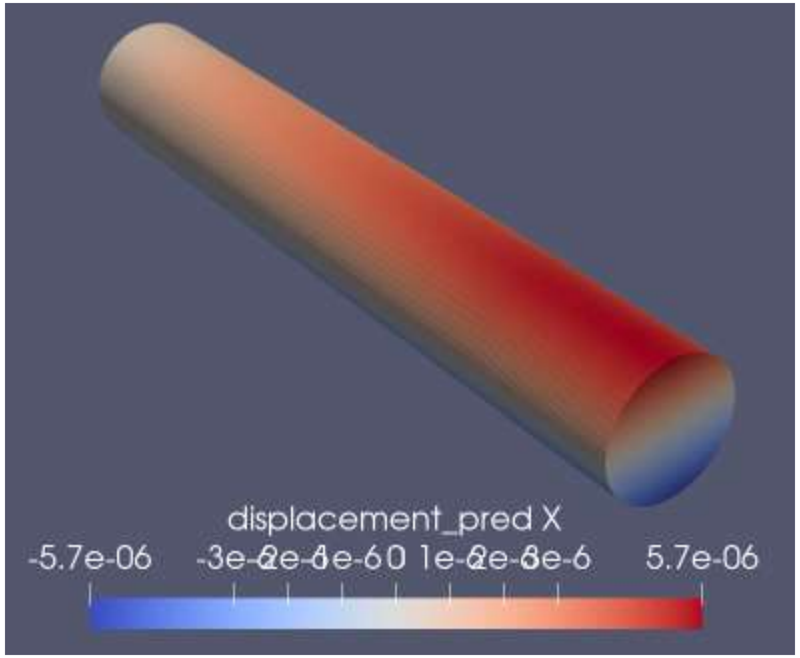


Circular section

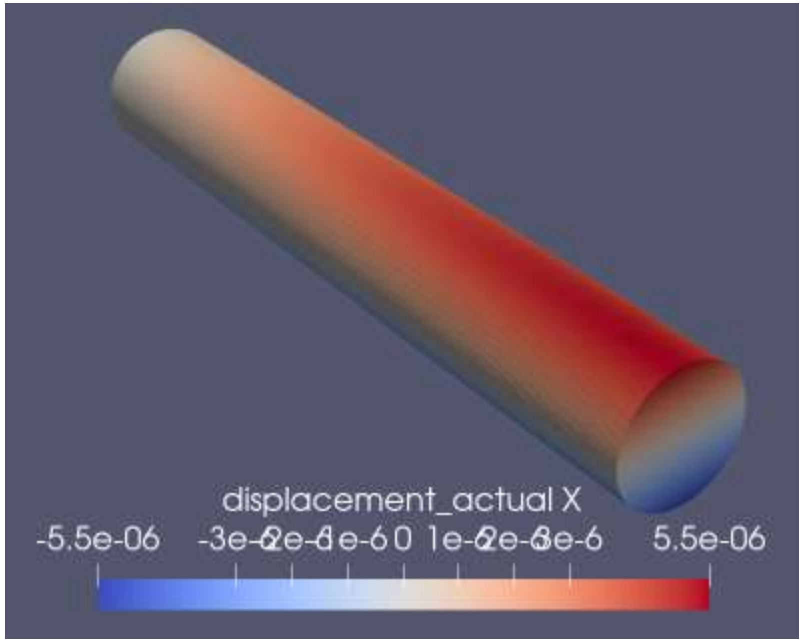
- Radius: 8
- Length: 100

Displacement X

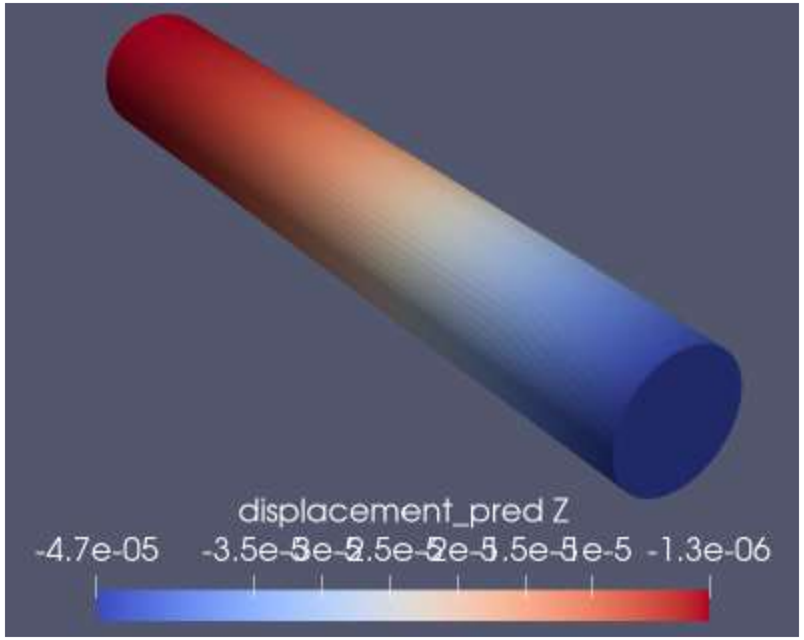
Predict

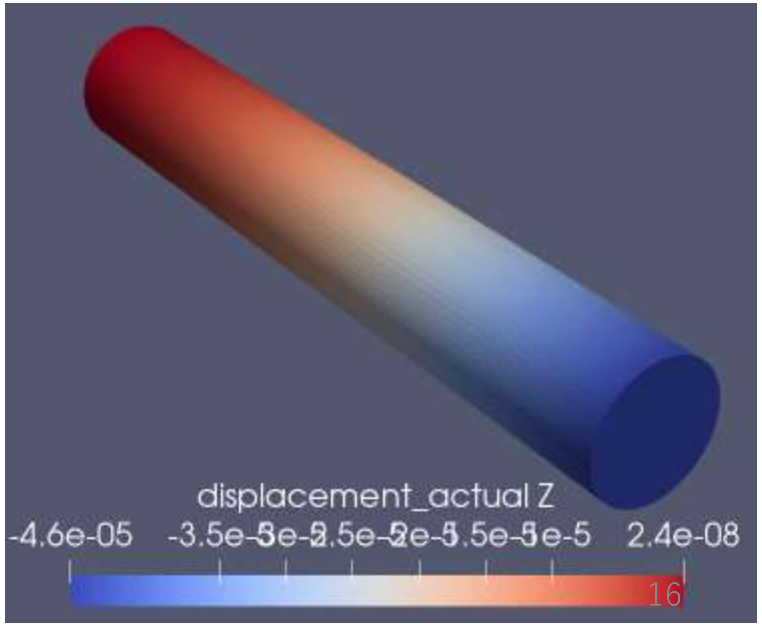


Actual

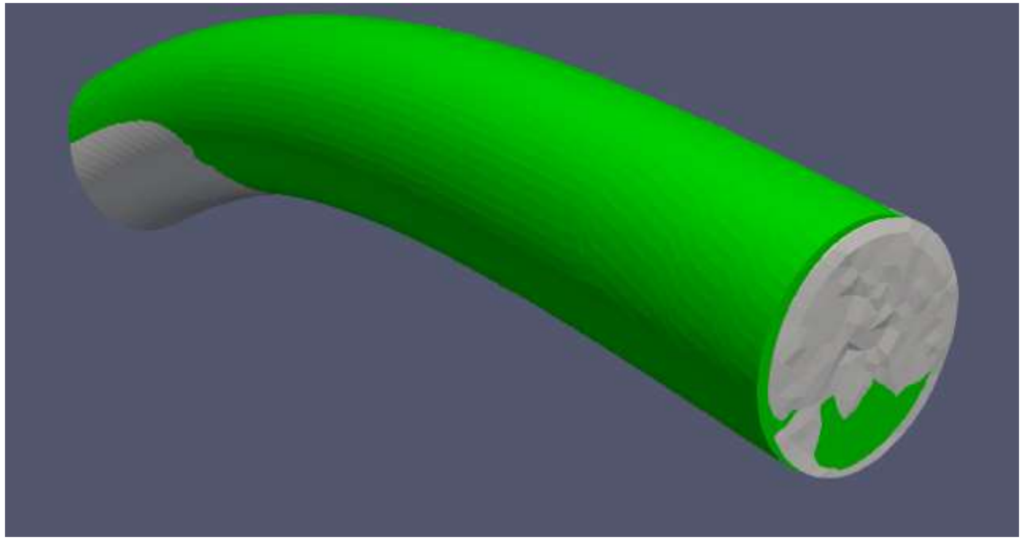


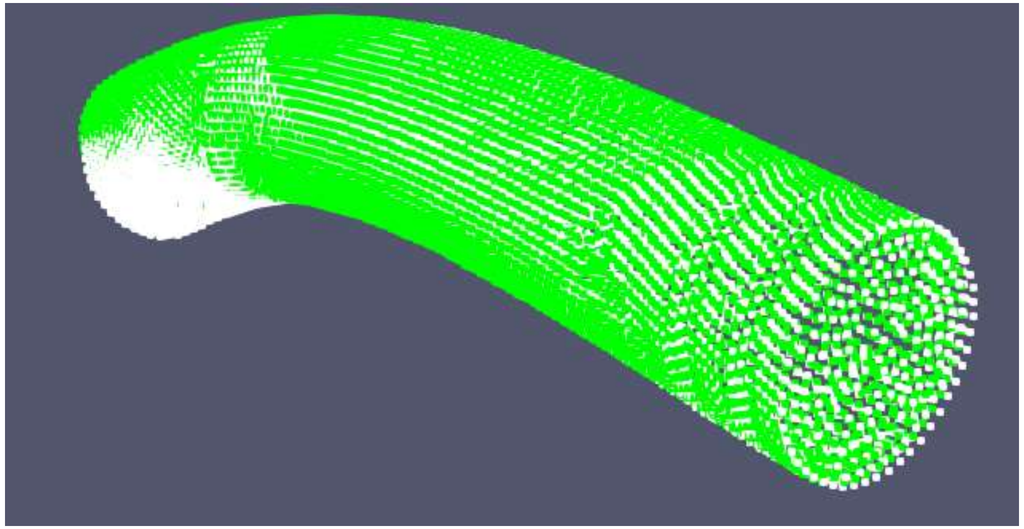
Displacement Z

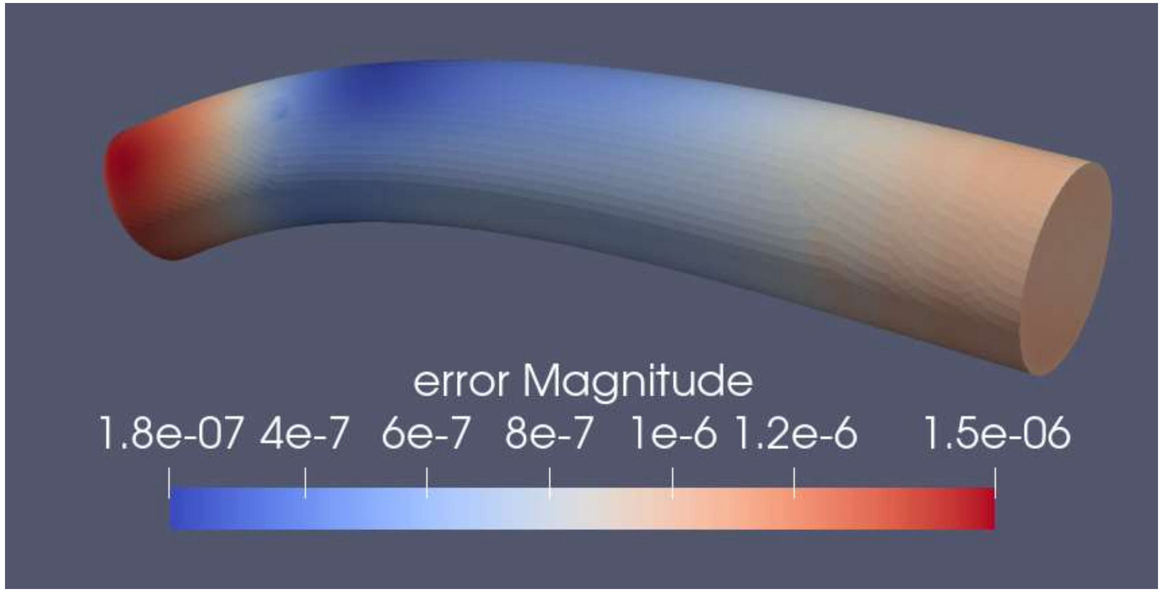




Deformation





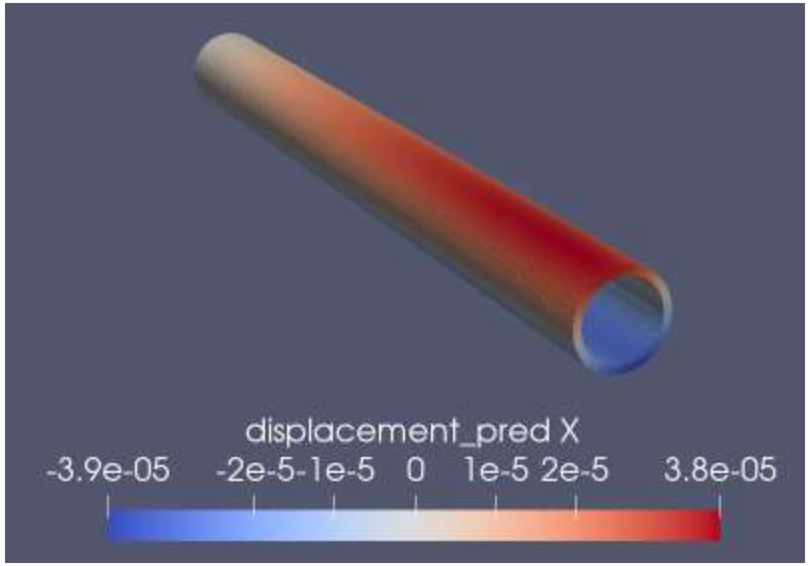


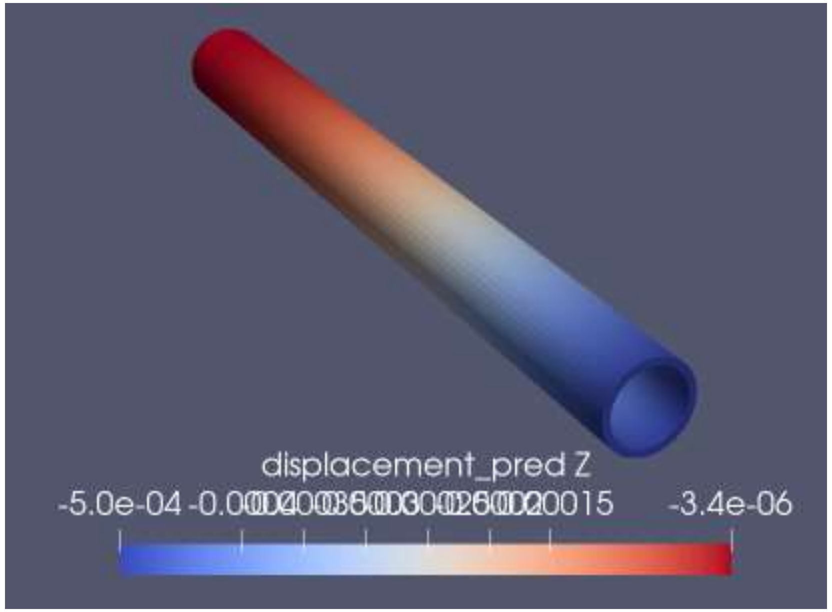
Hollow circular section
- Radius: 7.5
- Thickness: 1
- Length: 120

Displacement X

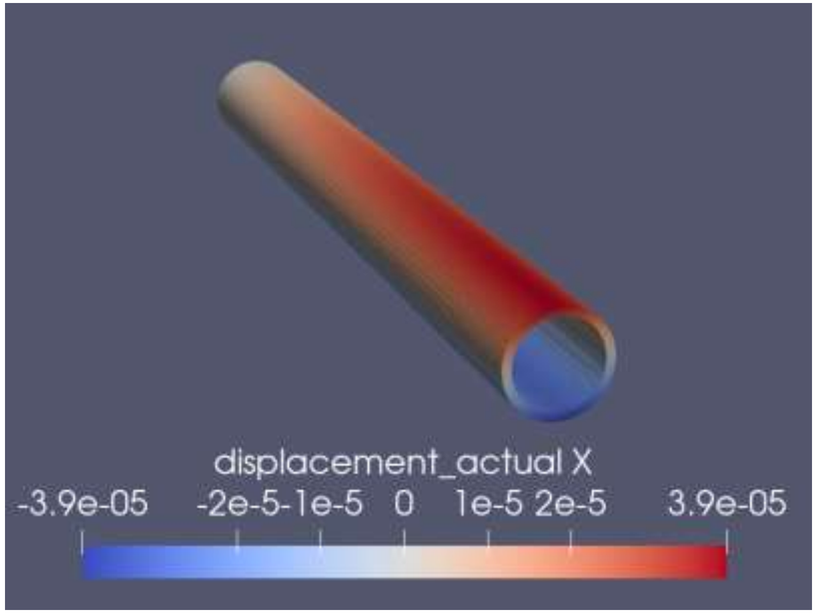
Displacement Z

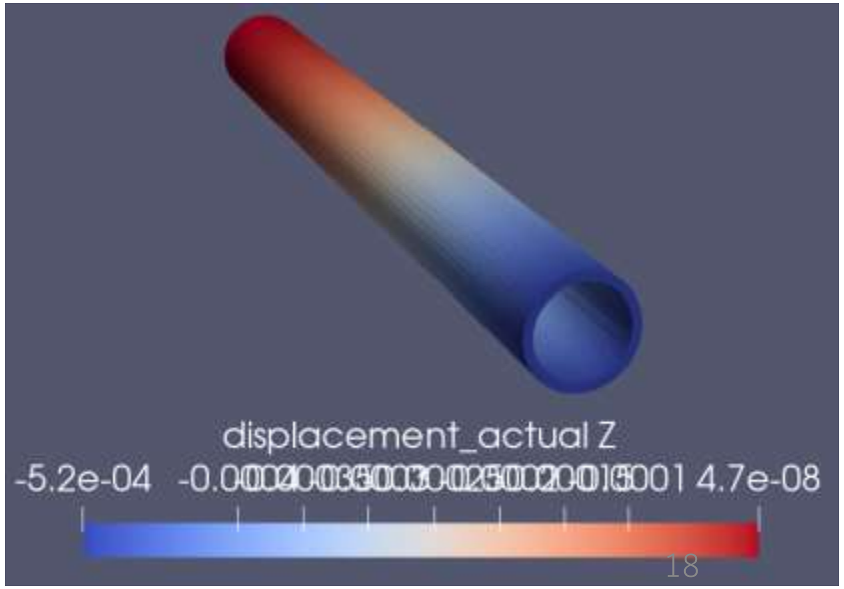
Predict



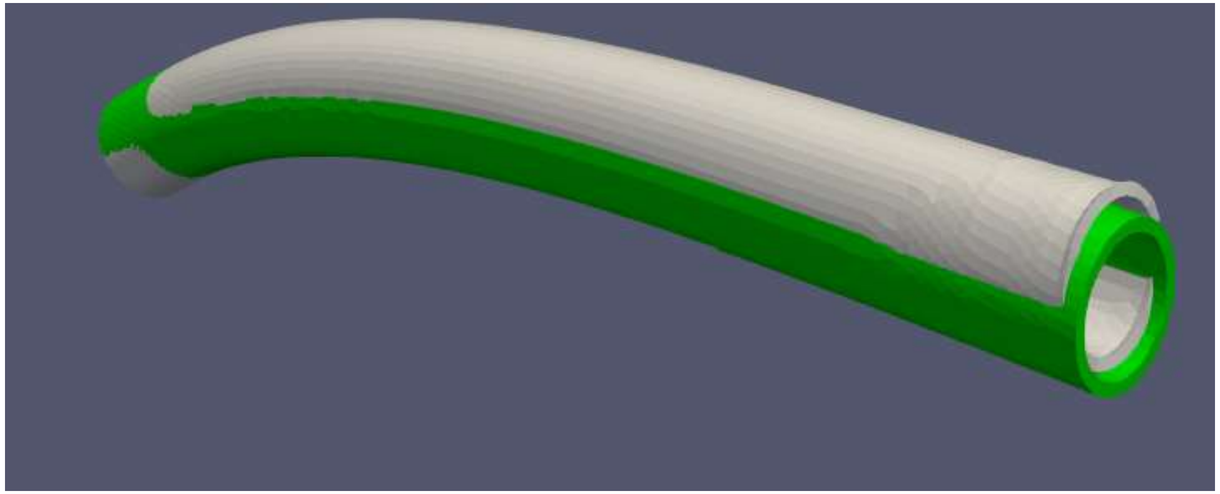


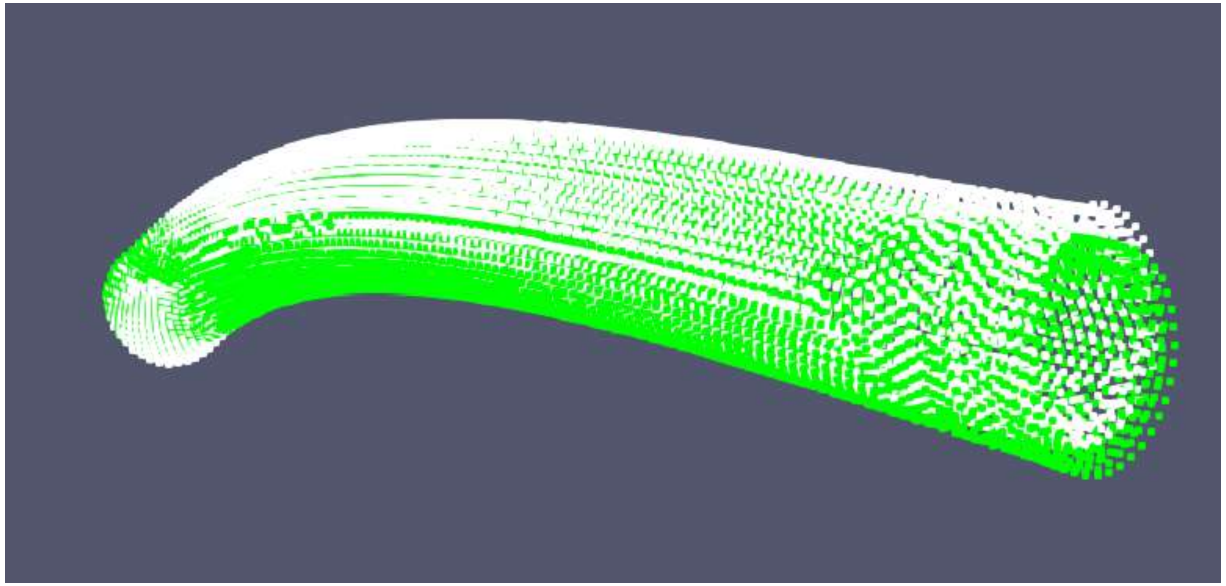
Actual

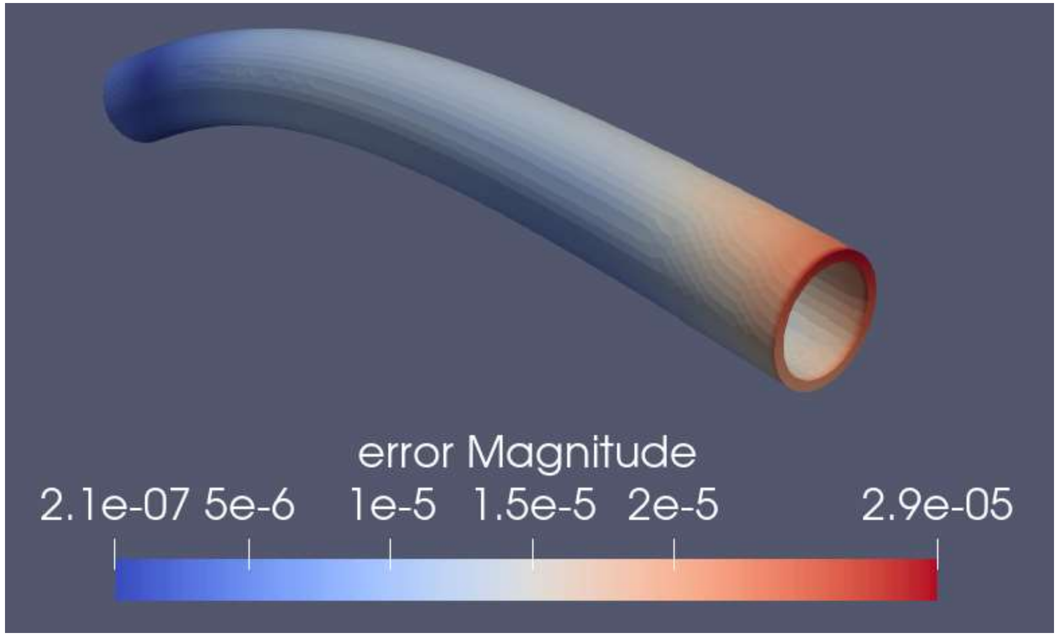




Deformation







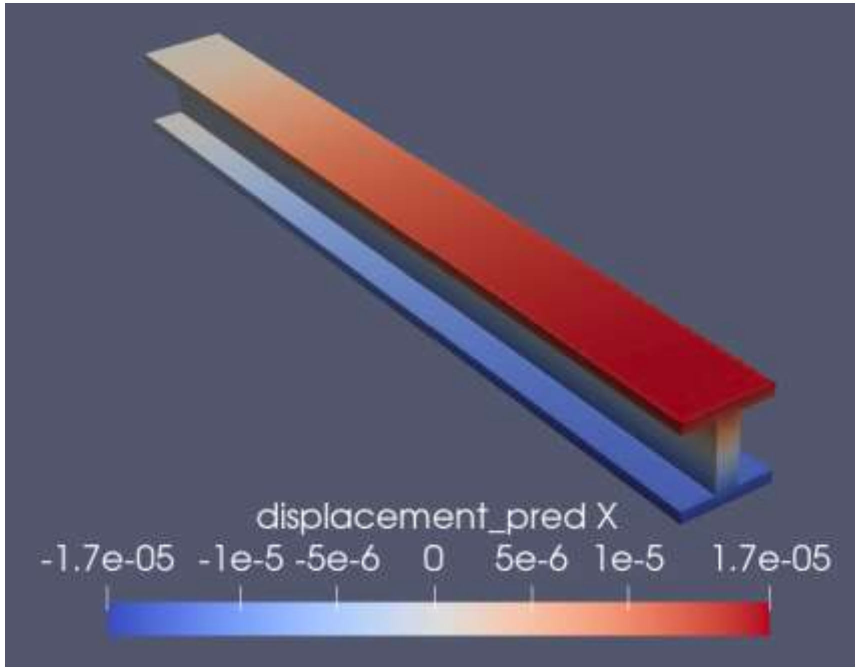
I shape section

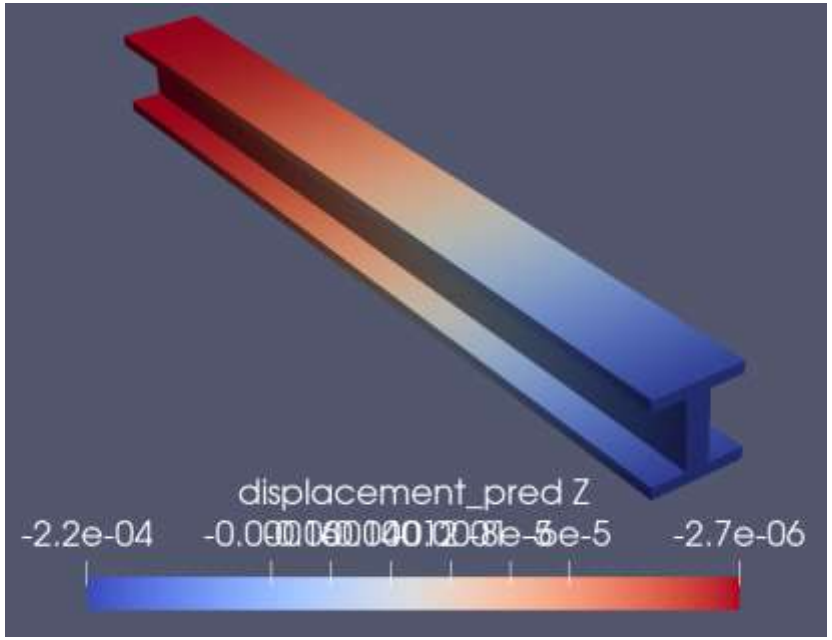
- Height: 12
- w: 12
- t1: 3
- t2: 1.5
- Length: 120

Displacement X

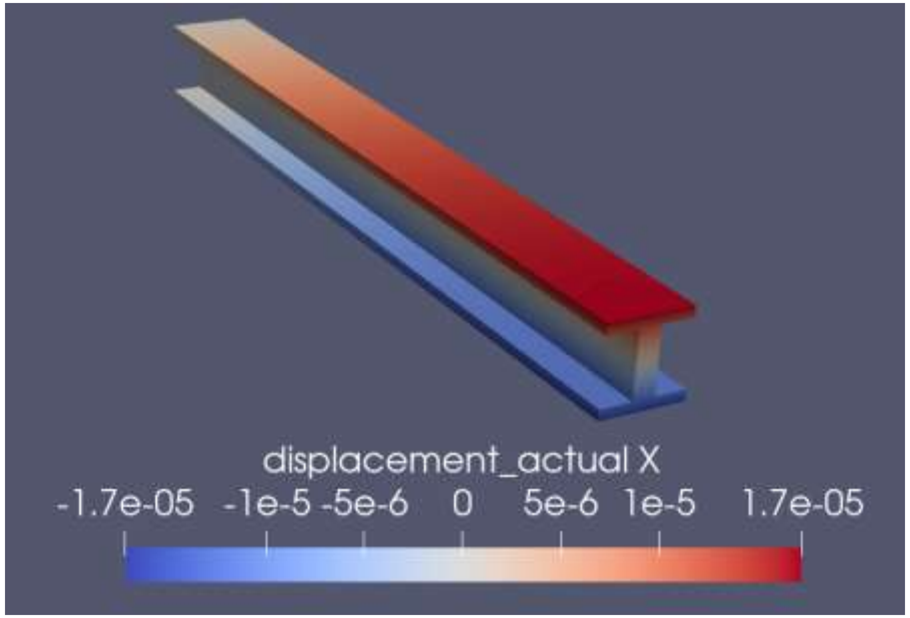
Displacement Z

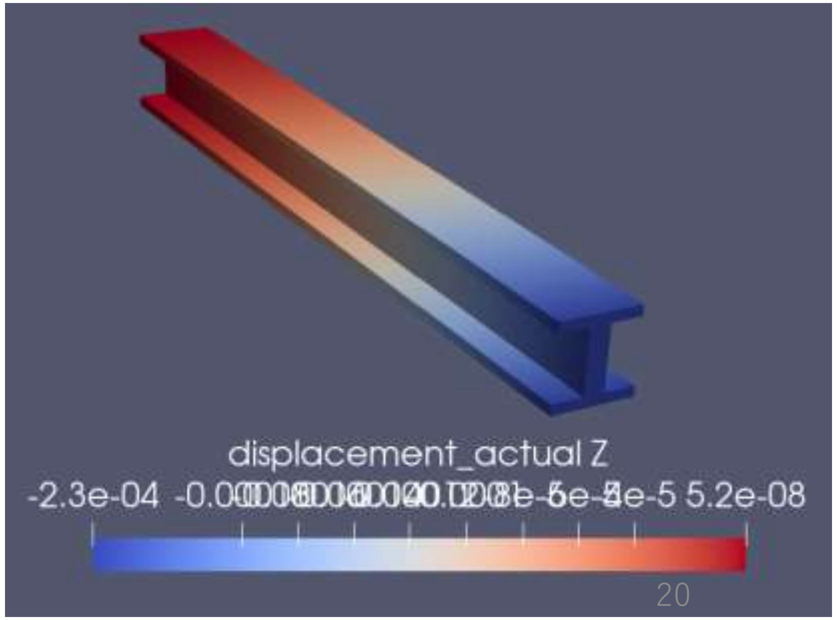
Predict



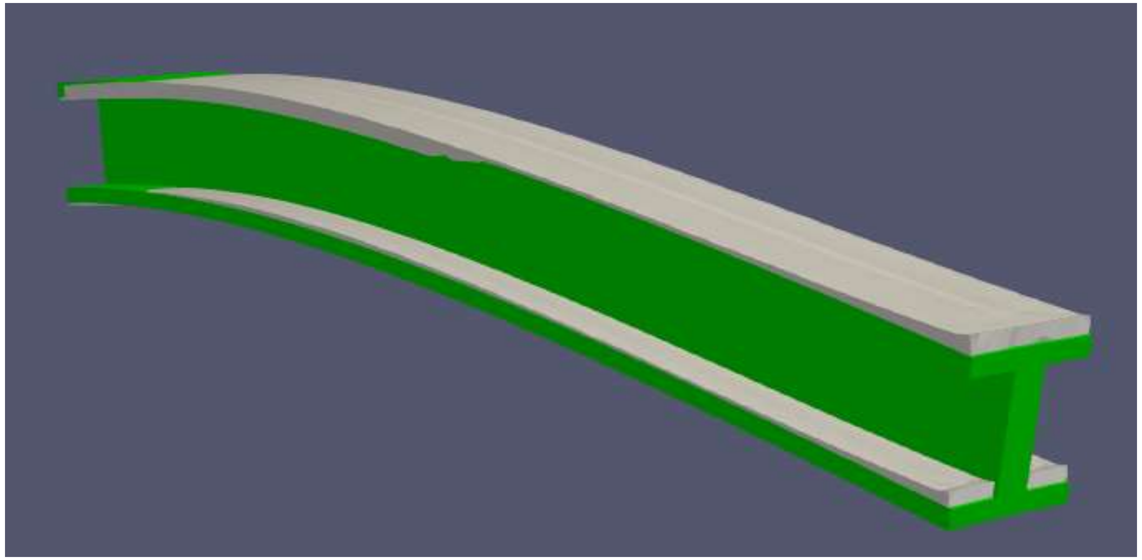


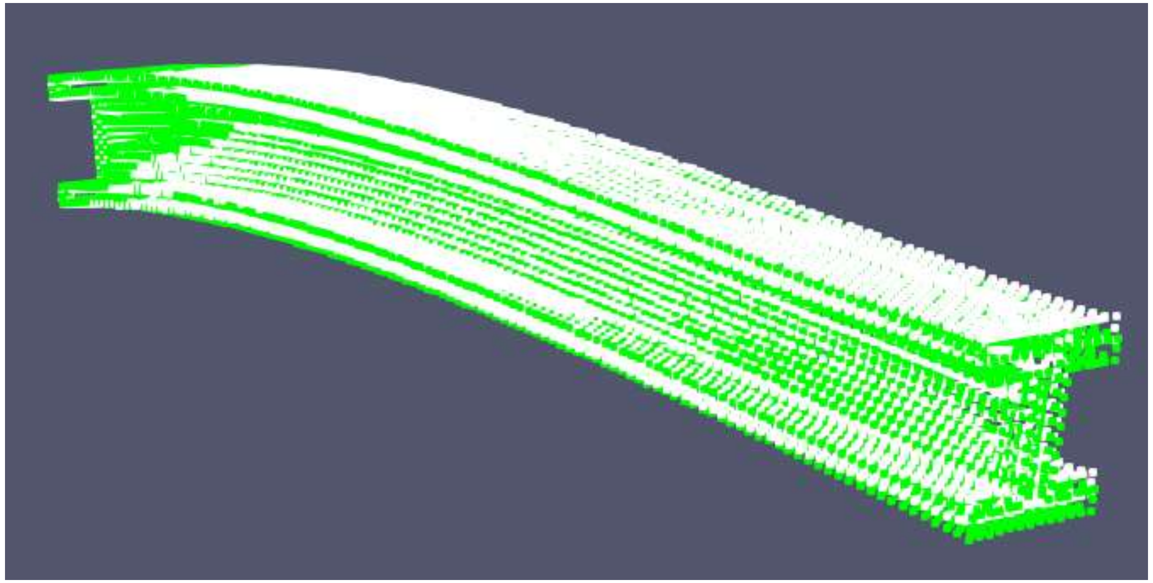
Actual

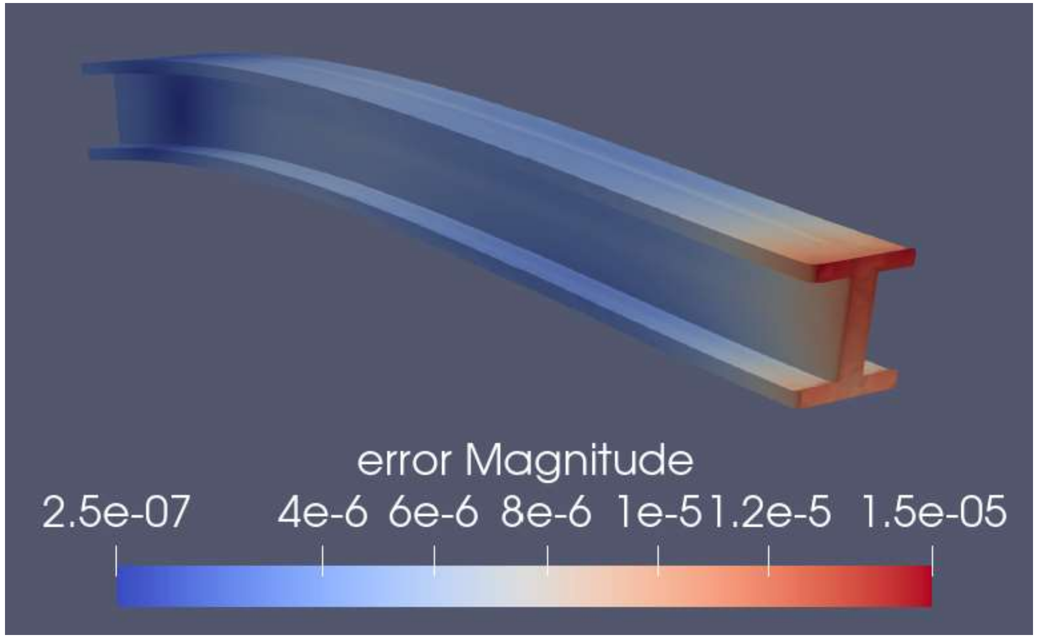




Deformation







Displacement prediction results (Unknown Model)

- The trained surrogate model is utilized to validate prediction results in an unknown model characterized by geometry dimensions not included in the training.
- The predicted results are compared across the five geometries listed in the table below. There is excellent agreement with the FEM results (Actual: reference value) for W (displacement in the Z direction) at the right end (free end).
- Detailed results, including displacement contour plots in the x-direction, displacement contour plots in the z-direction, deformation diagram comparisons, and error distribution contour plots, are provided (pages 23 and following).

Cross-section	Z disp. (ref. value)	Z disp. (Predicted)	Error	Note
Rectangular	-3.70E-04	-4.40E-04	0.19	Height: 6,Width: 6,Length: 65
Hollow rectangular	-4.00E-04	-4.00E-04	0.00	Height: 10,Width: 5,Thickness: 1,Length: 90
Circular	-5.60E-05	-4.80E-05	0.14	Radius: 8,Length: 105
Hollow circular	-6.60E-05	-6.10E-05	0.08	Radius: 8,Thickness: 1.5,Length: 90
I shape	-1.60E-04	-1.60E-04	0.00	Height: 11,w: 11,t1: 2,t2: 2,Length: 100

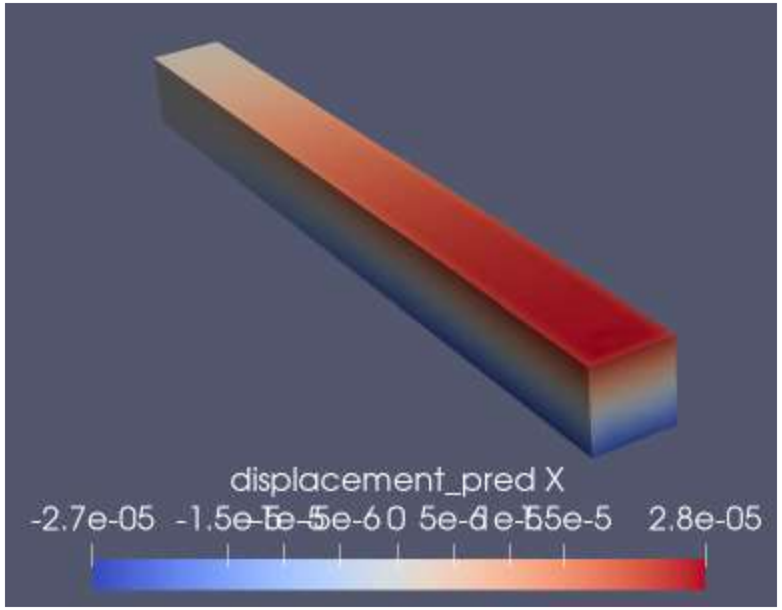
Rectangular section

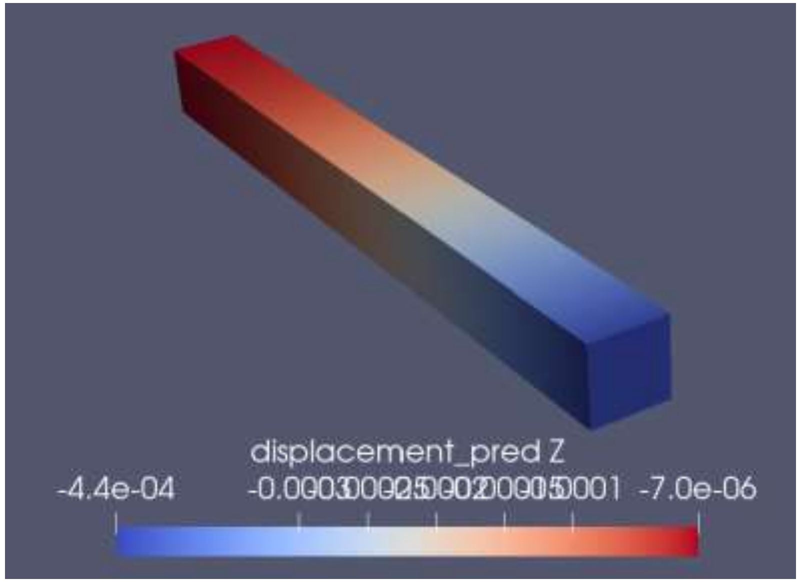
- Height: 6
- Width: 6
- Length: 65

Displacement X

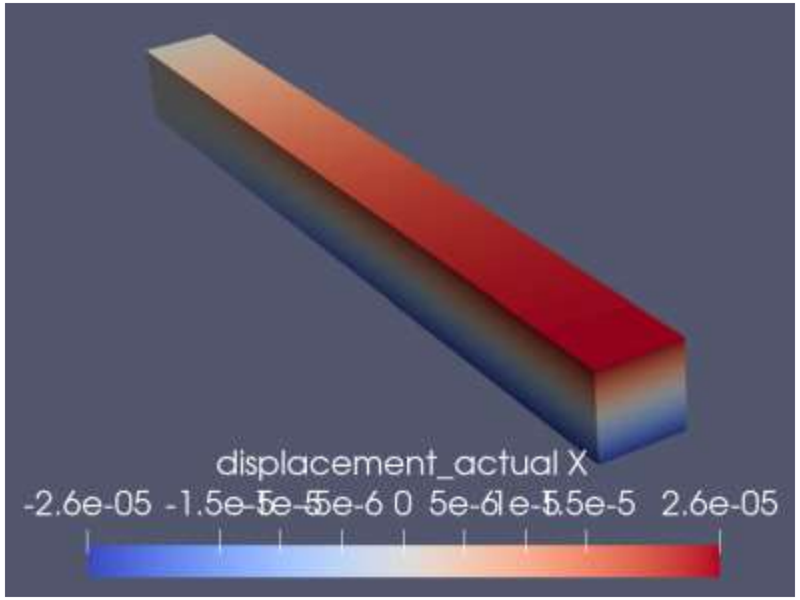
Displacement Z

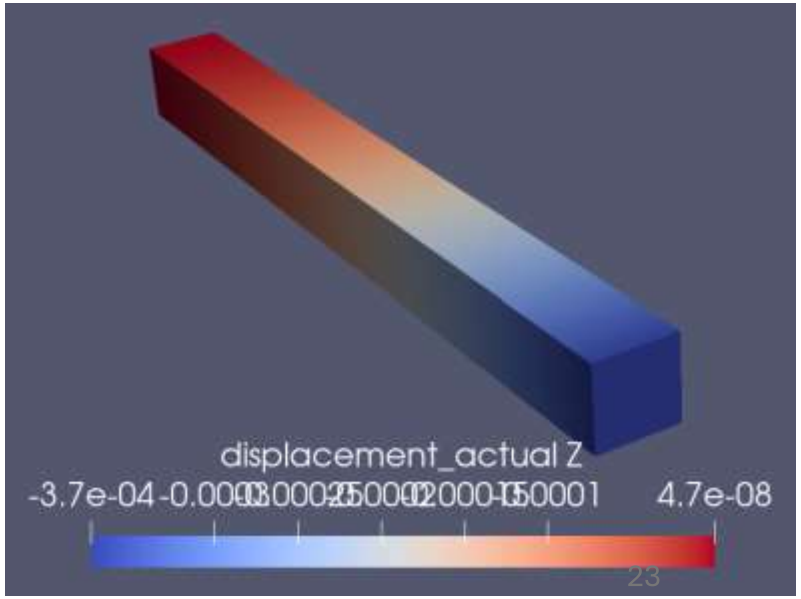
Predict



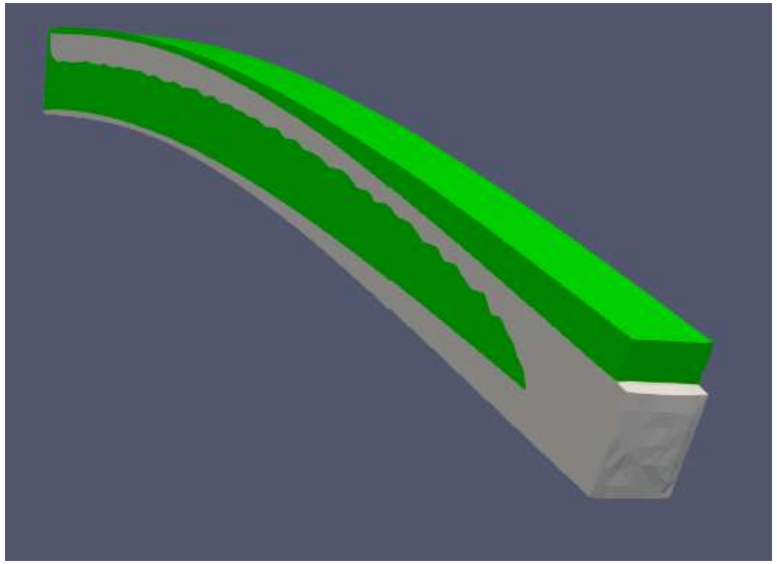


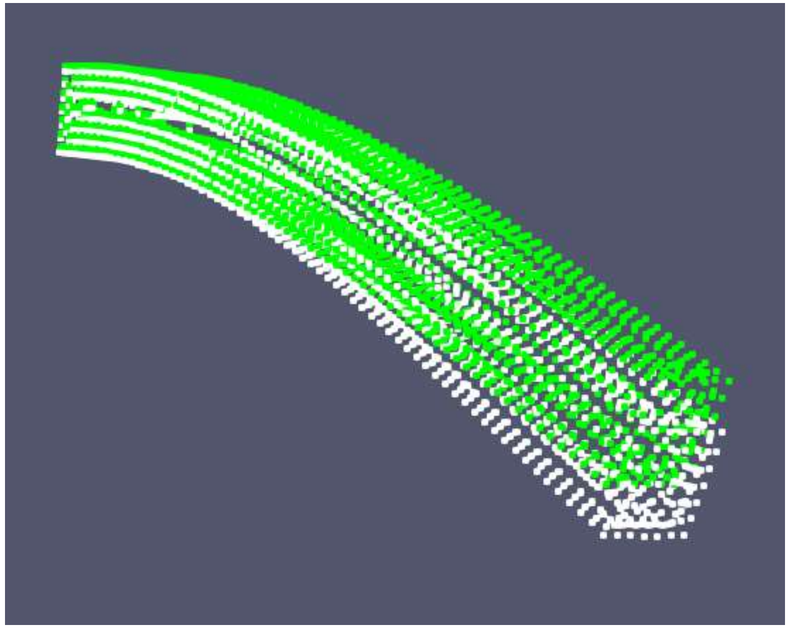
Actual

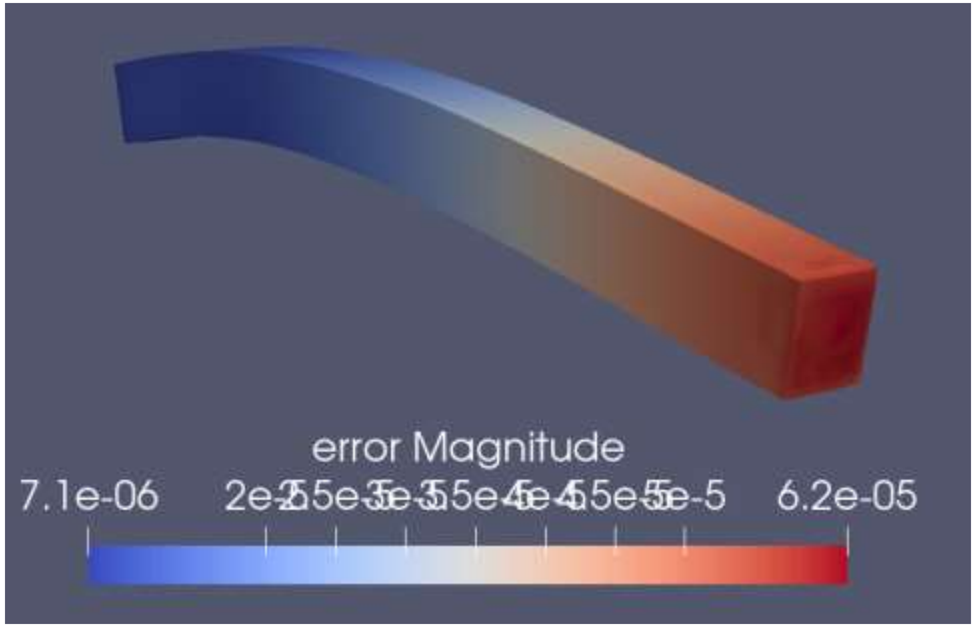




Deformation







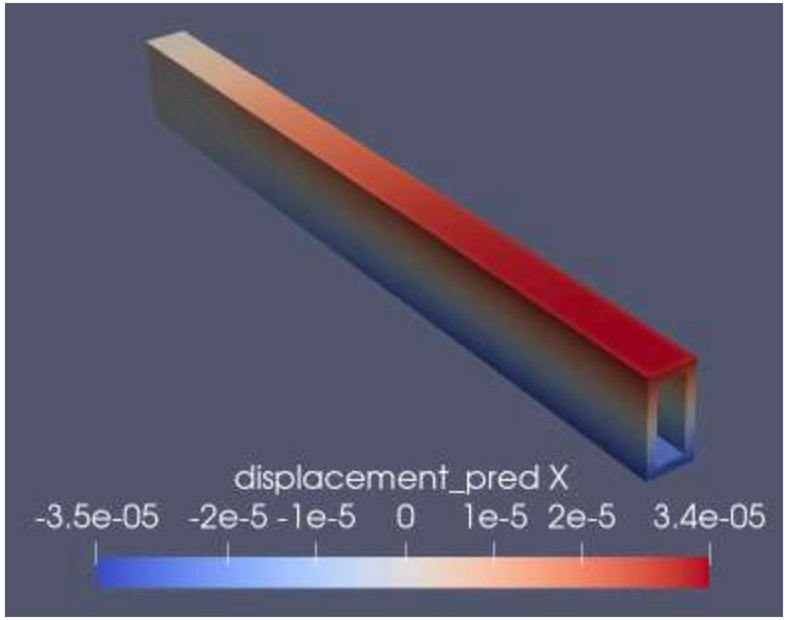
Hollow rectangular section

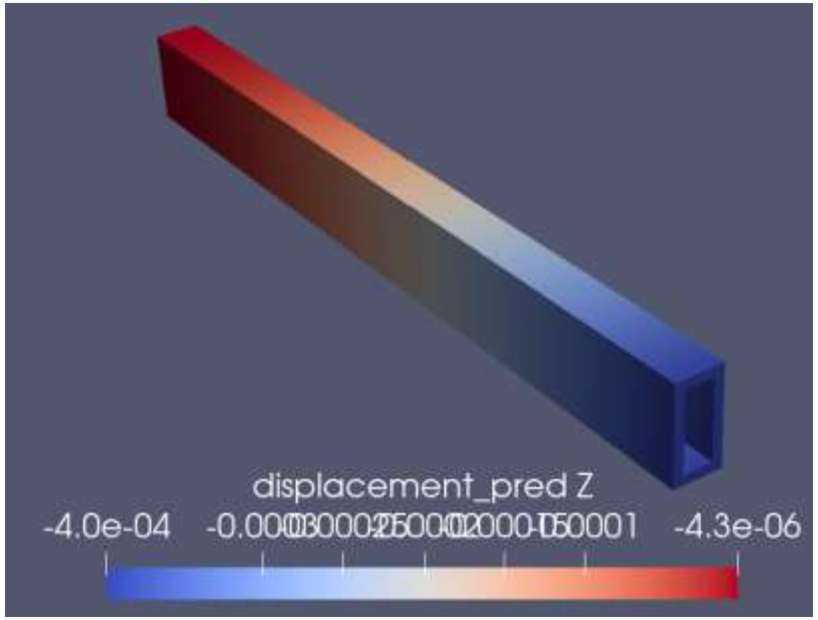
- Height: 10
- Width: 5
- Thickness: 1
- Length: 90

Displacement X

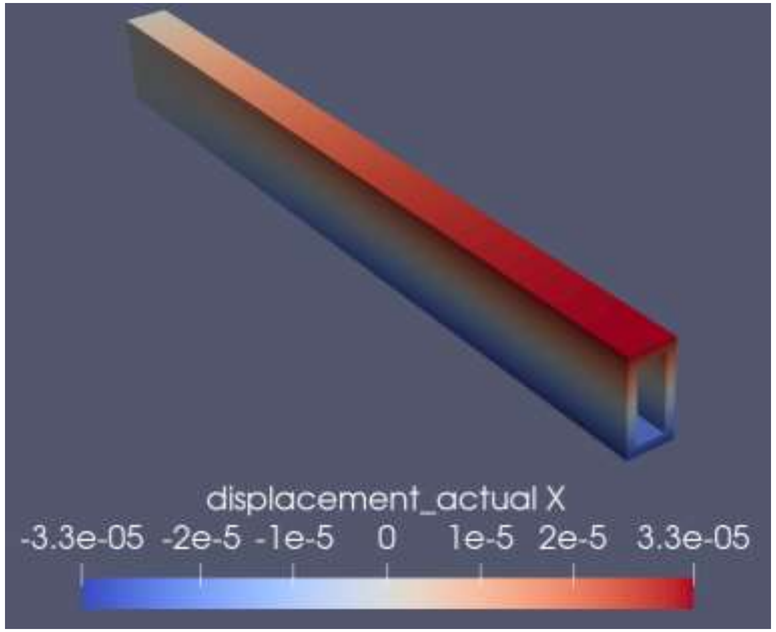
Displacement Z

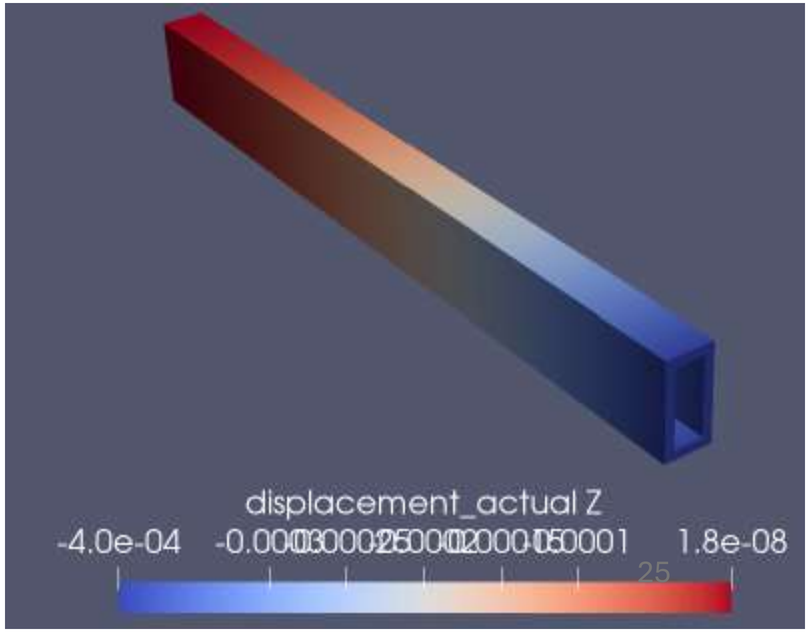
Predict



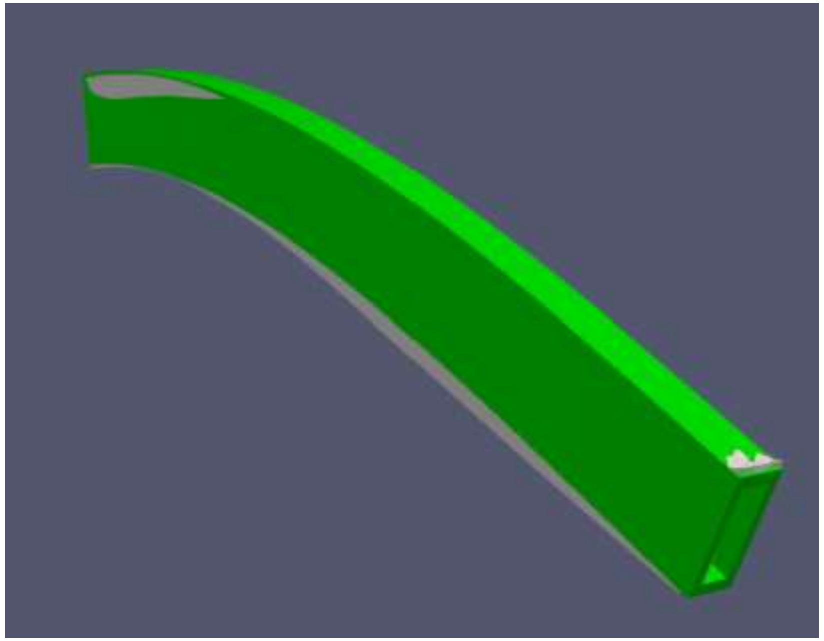


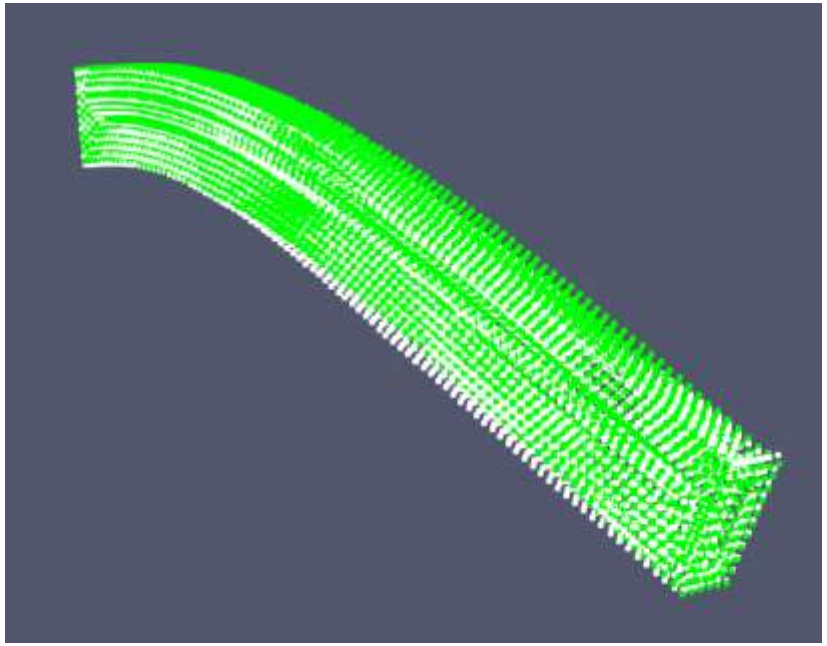
Actual

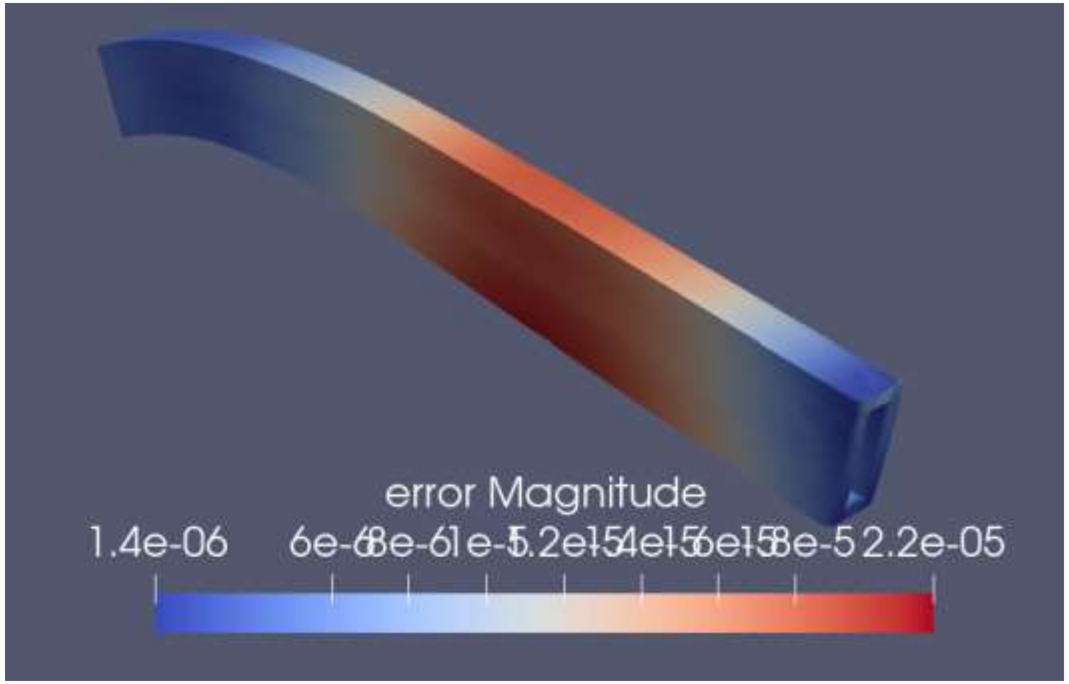




Deformation





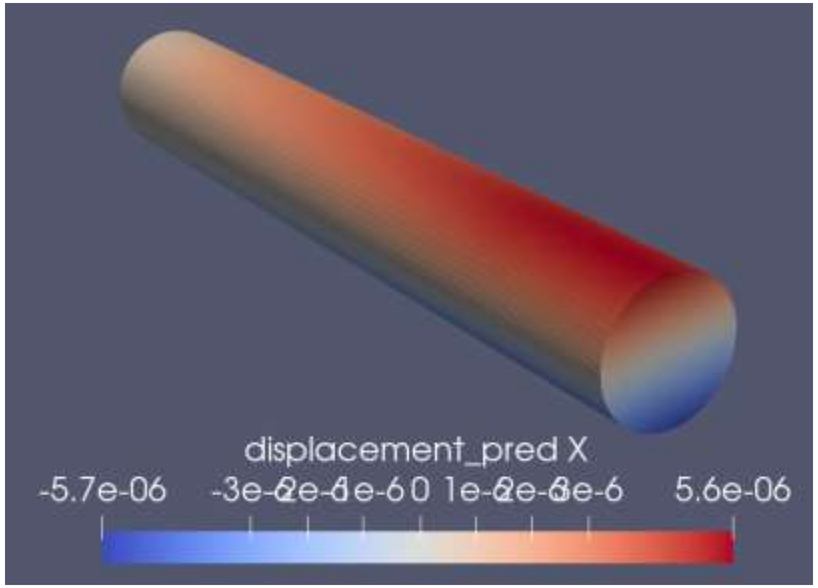


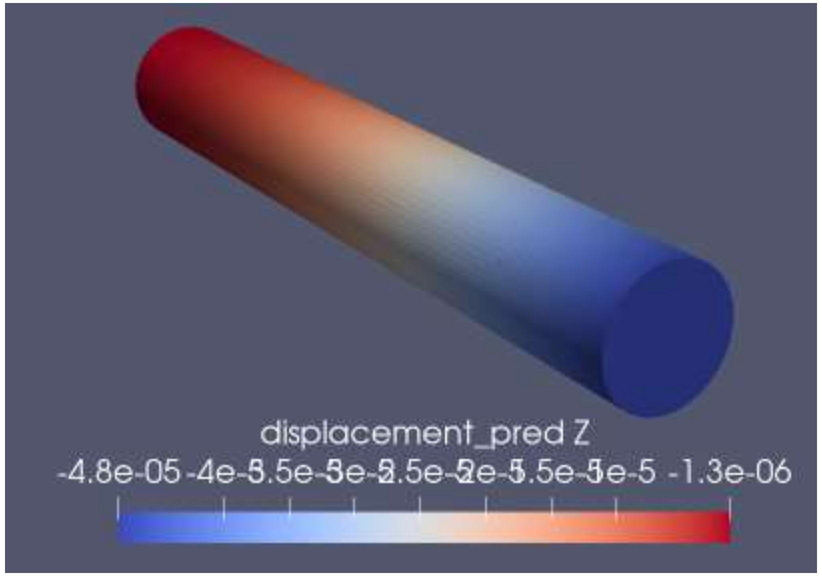
Circular section
- Radius: 8
- Length: 105

Displacement X

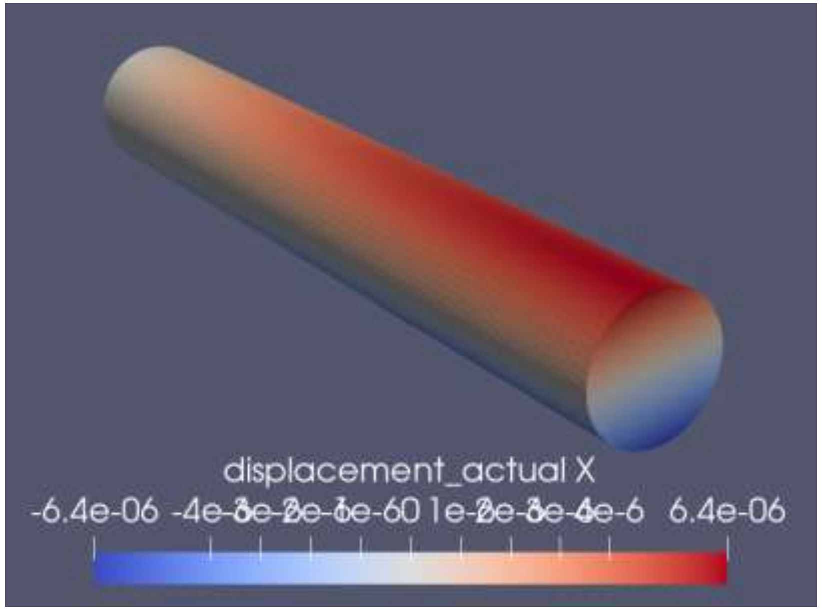
Displacement Z

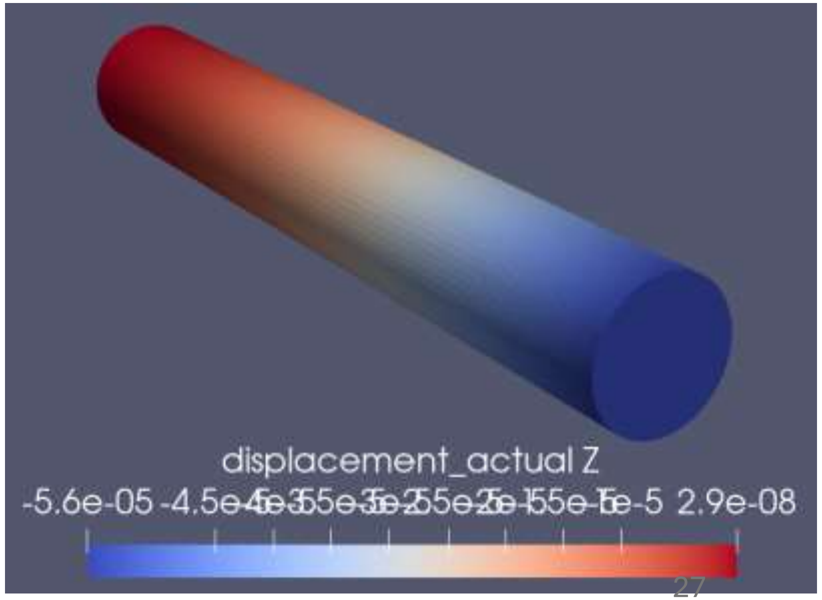
Predict



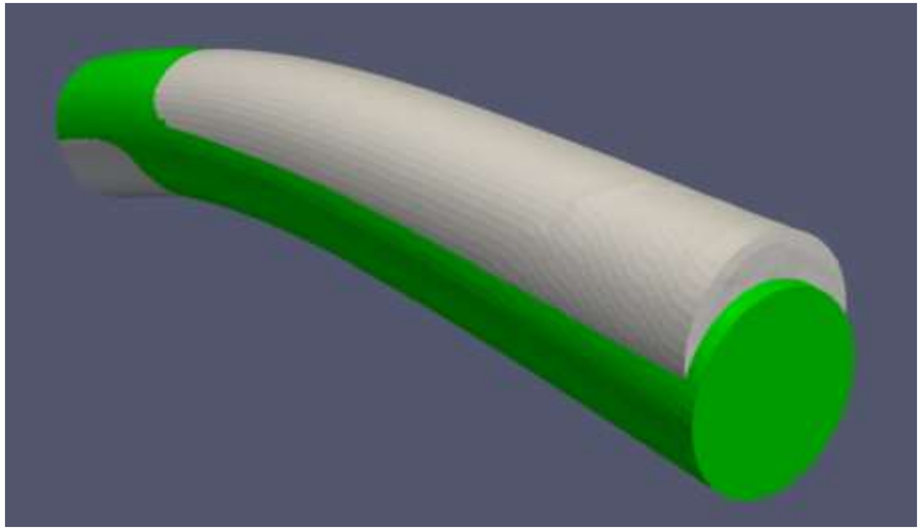


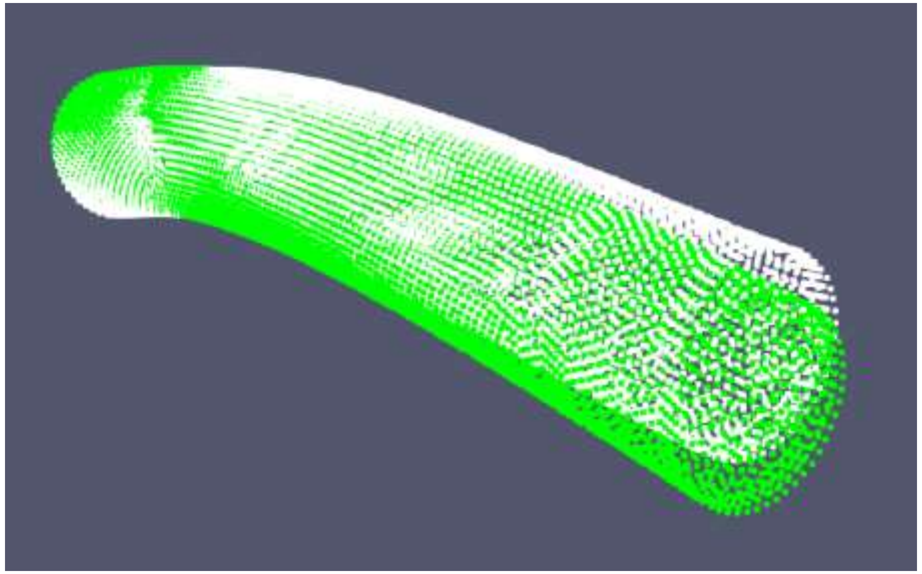
Actual

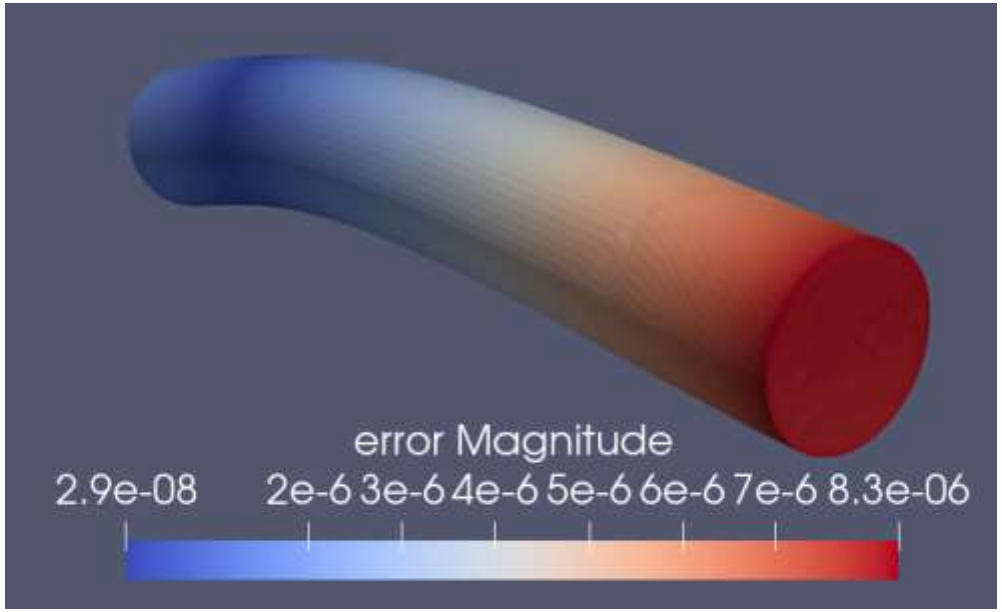




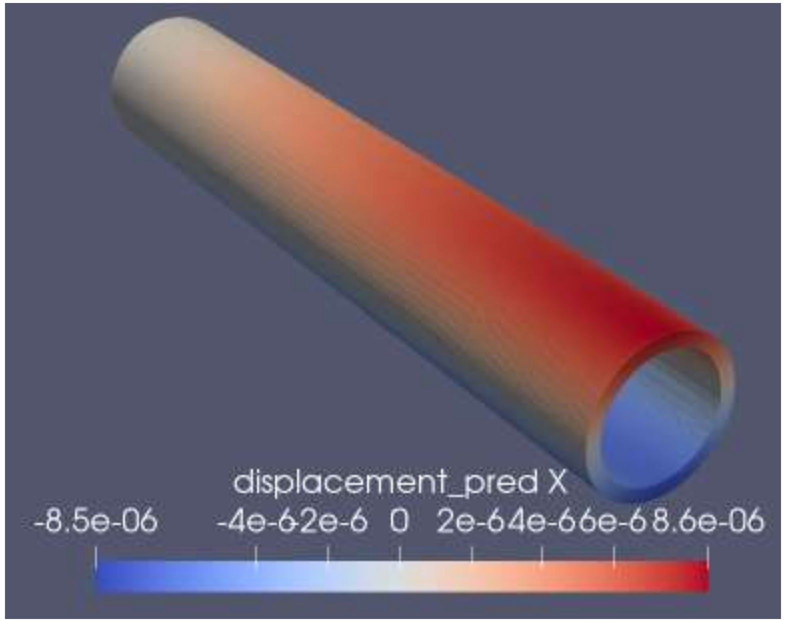
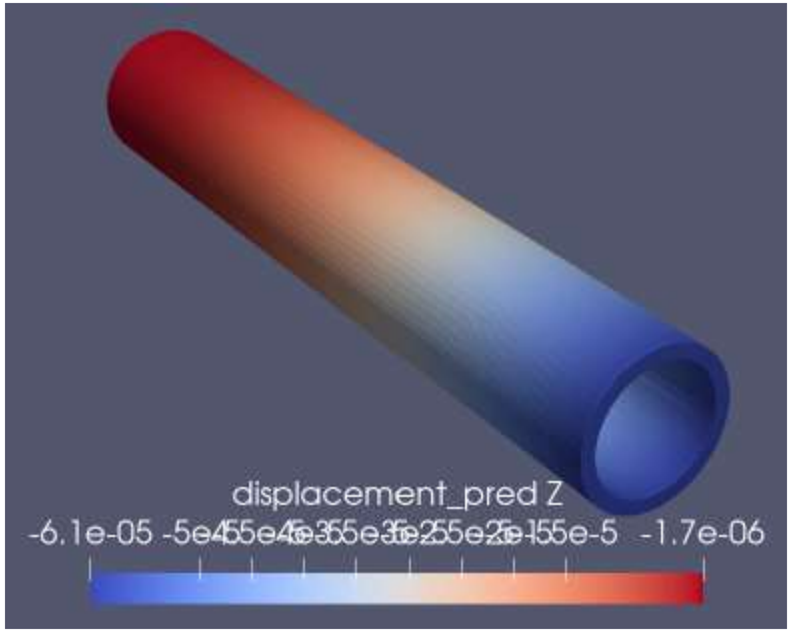
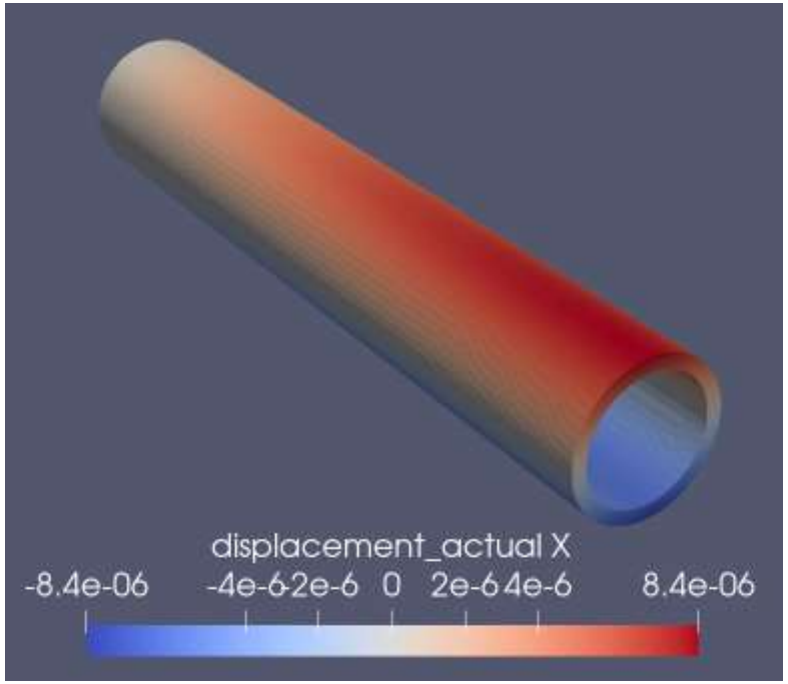
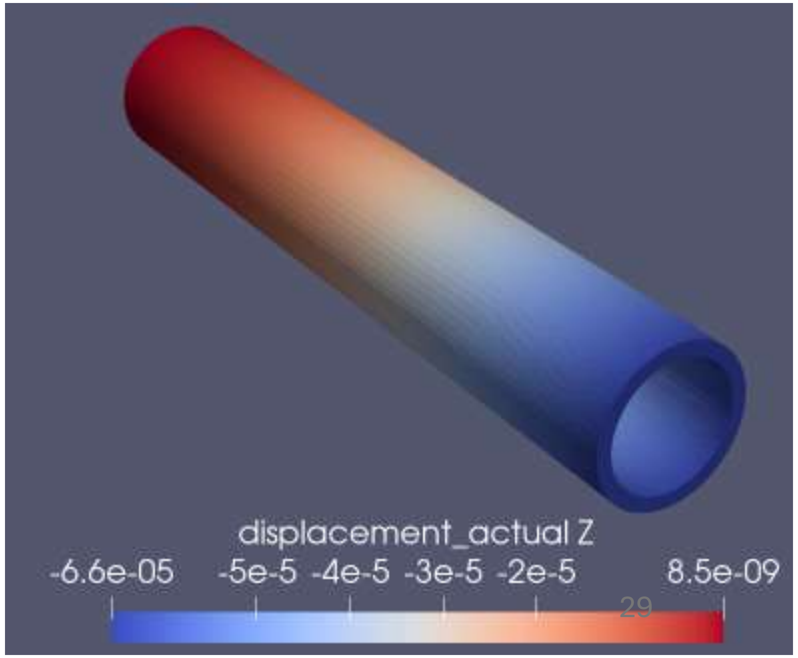
Deformation



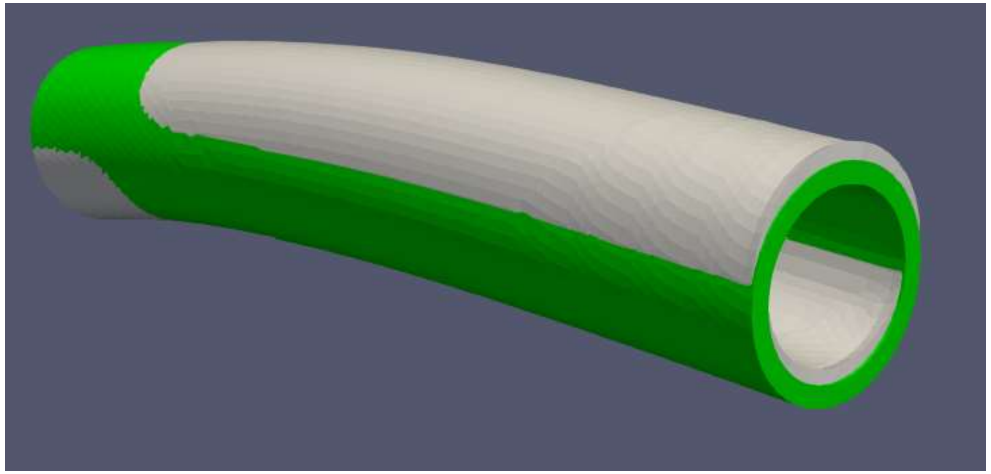


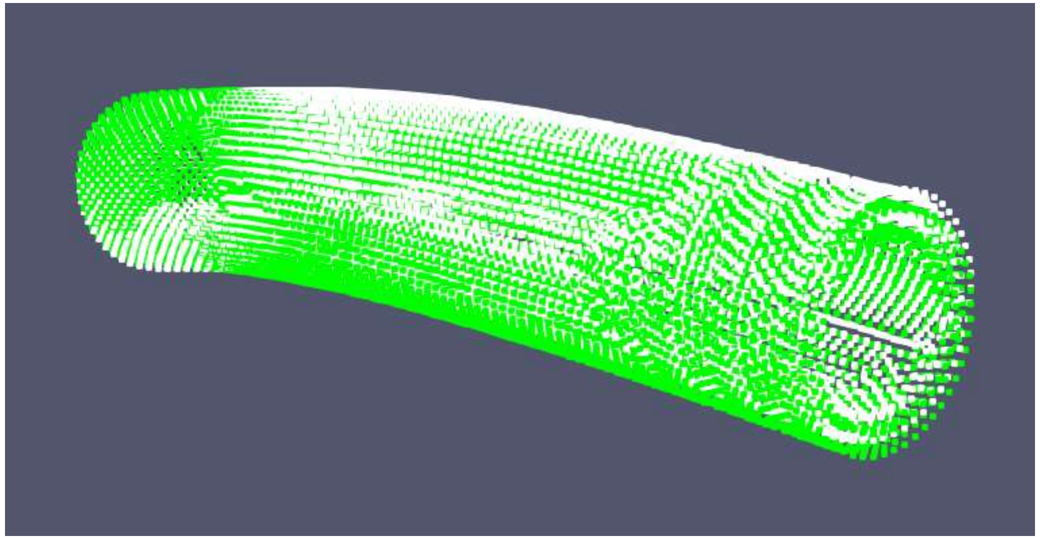


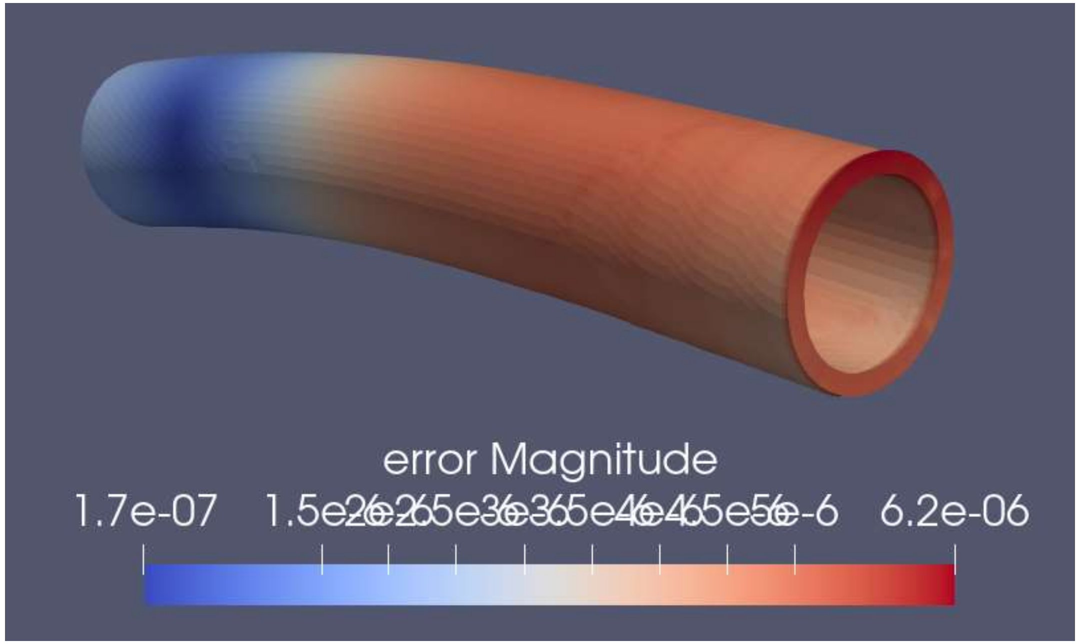
Hollow circular section
- Radius: 8
- Thickness: 1.5
- Length: 90

	Displacement X	Displacement Z
Predict		
Actual		

Deformation





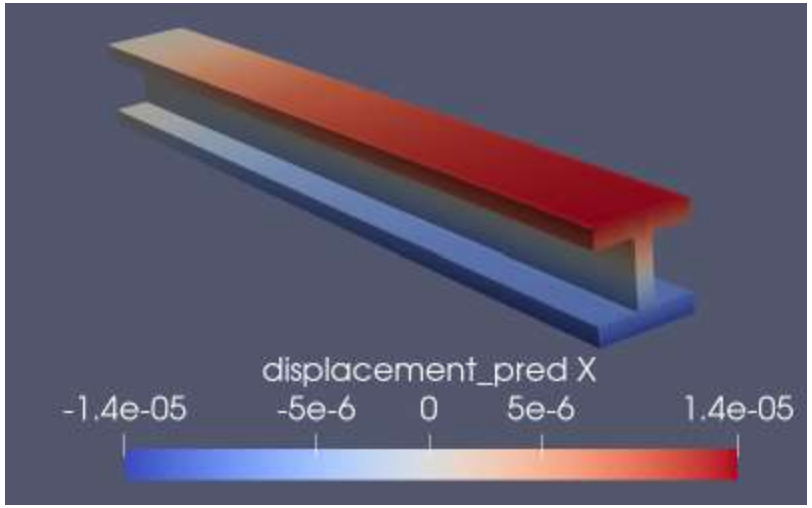


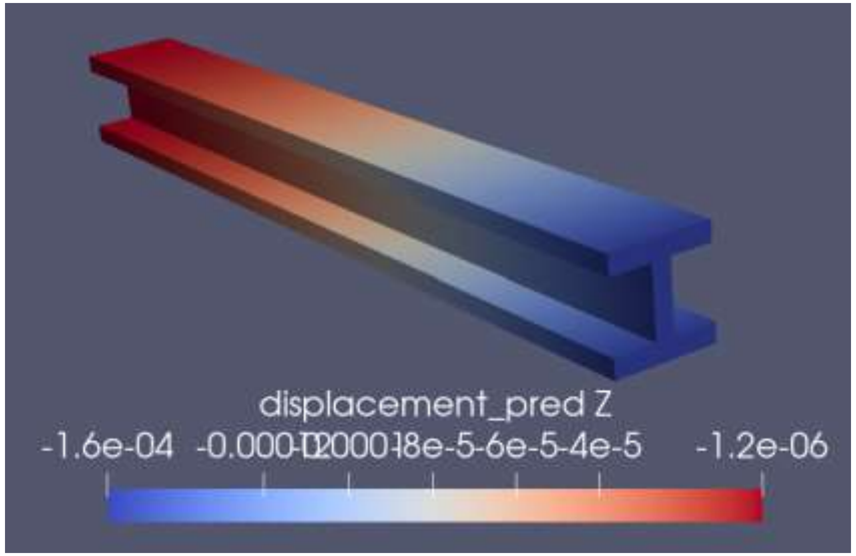
I shape section

- Height: 11
- w: 11
- t1: 2
- t2: 2
- Length: 100

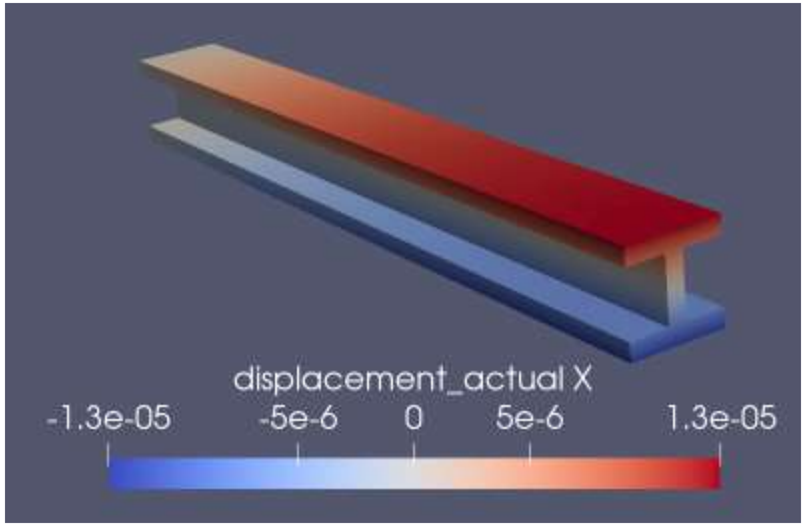
Displacement X | Displacement Z

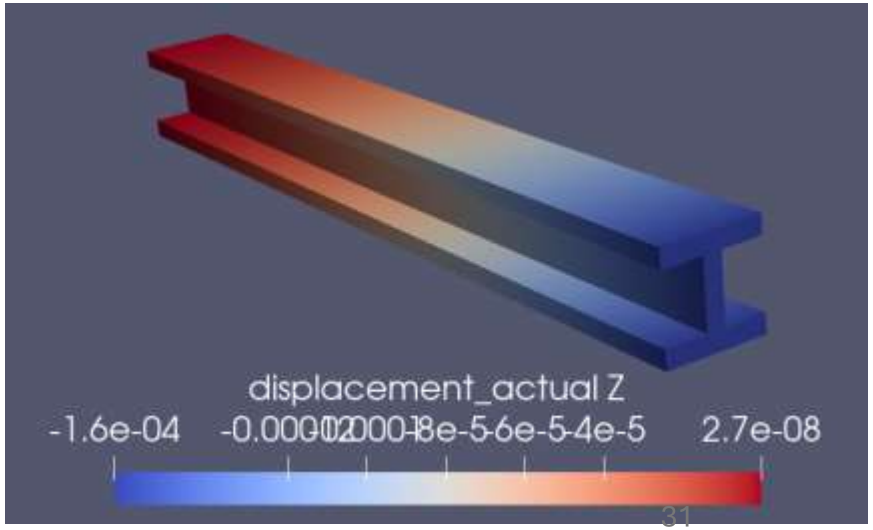
Predict



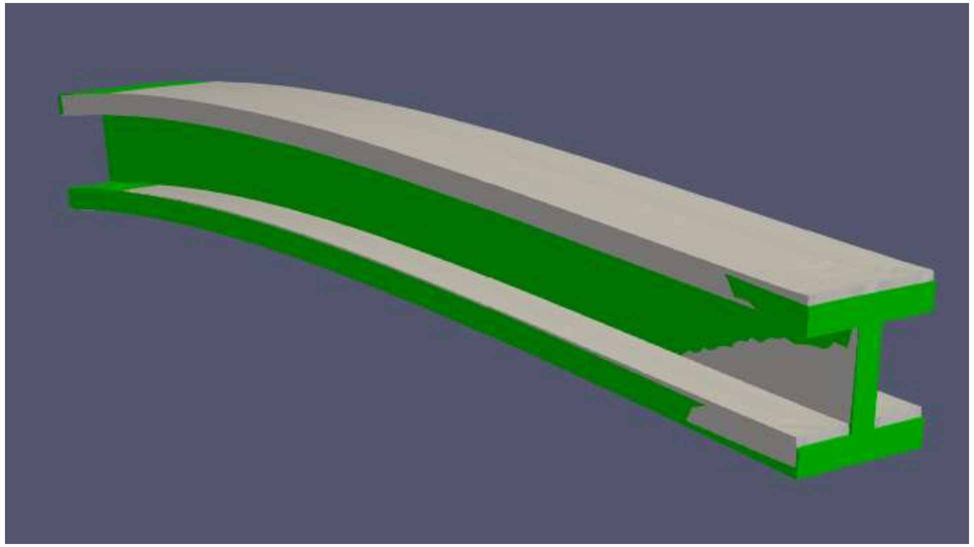


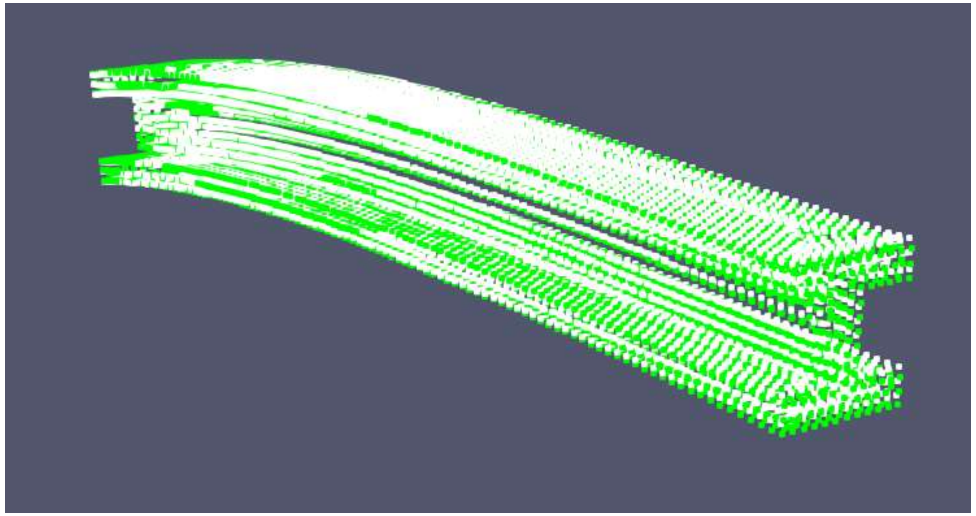
Actual

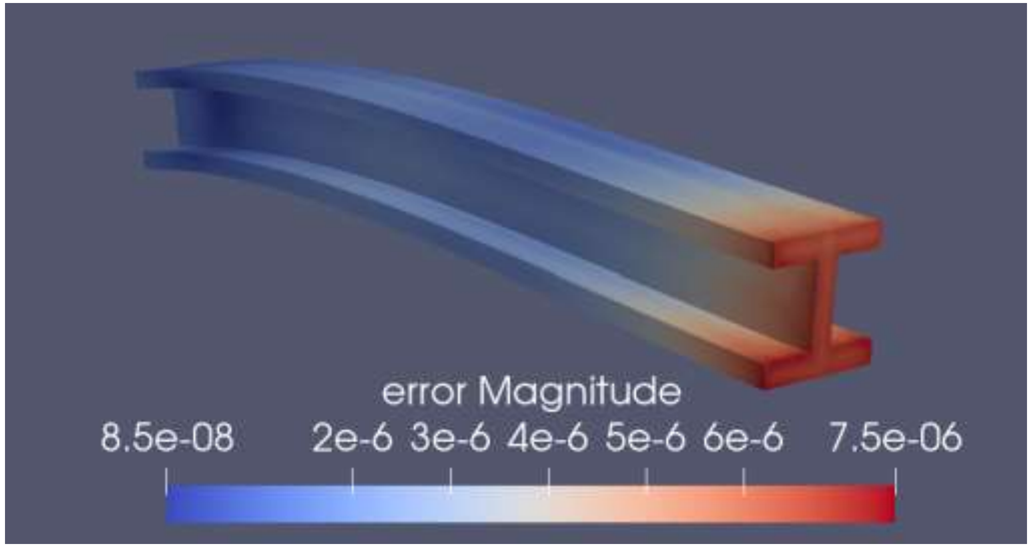




Deformation







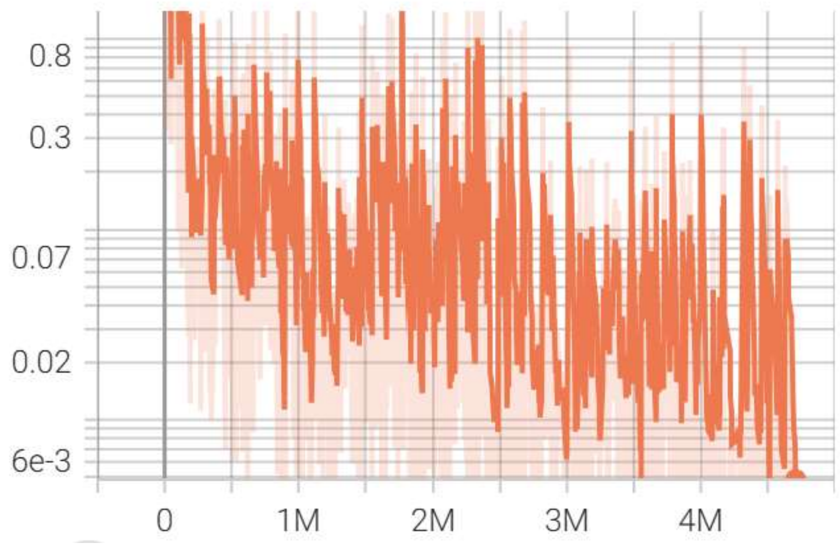
Stress prediction AI model

Training

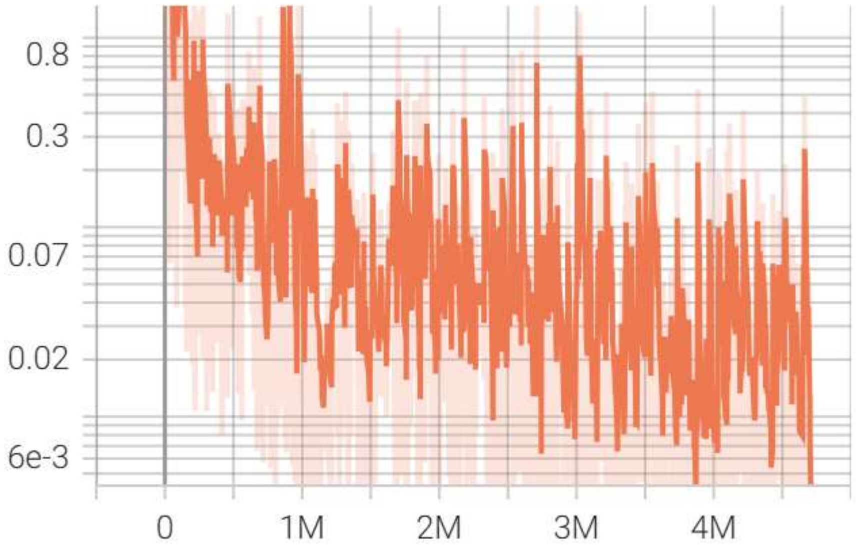
- The graphs of overall loss (Train loss) and Mises stress (Mises) depict the evolution of the loss function during training.
- The overall loss averaged for each epoch(*) is displayed below the plot (page 35).
- The x-axis of the graph indicates the number of iterations; it appears to oscillate when all iteration values are used, while the graph averaged for each epoch converges smoothly.

*1 epoch = 325 iterations

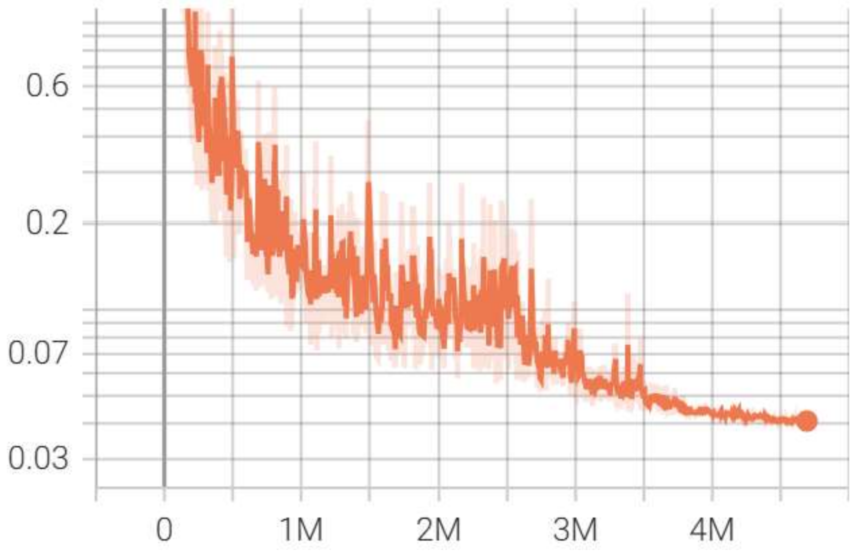
train_loss
tag: train_loss



mises
tag: mises



epoch_train_loss
tag: epoch_train_loss



Stress prediction results (known model)

- The trained surrogate model is used to validate the predicted results in the known model, corresponding to the shape dimensions utilized during training.
- The predicted results are compared across the five geometries presented in the table below. There is excellent agreement with the FEM results (Actual: reference value) for the maximum Mises stress at the left end (constrained end).
- A detailed discussion of the results is presented in the Mises Stress Contour Diagram Comparison (page 37 and following).

Cross-section	Mises stress (ref.)	Mises stress (predicted)	Error	Note
Rectangular	3.30E+07	3.10E+07	0.06	Height: 15,Width: 10,Length: 120
Hollow rectangular	6.80E+07	6.30E+07	0.07	Height: 10,Width: 15,Thickness: 1.5,Length: 120
Circular	3.00E+07	3.00E+07	0.00	Radius: 7.5,Length: 110
Hollow circular	1.30E+08	1.20E+08	0.08	Radius: 7.5,Thickness: 1,Length: 120
I shape	5.90E+07	5.90E+07	0.00	Height: 12,w: 12,t1: 3,t2: 1.5,Length: 120

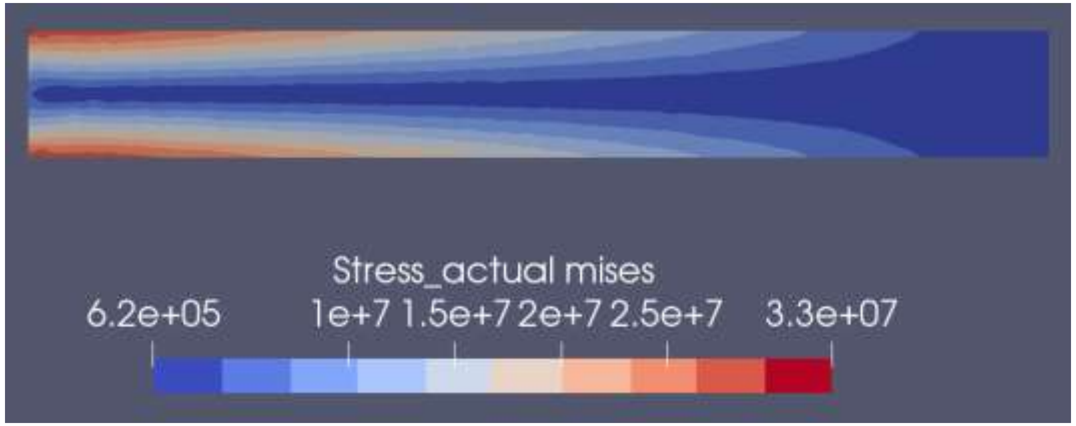
Stress Mises

Rectangular section

- Height: 15
- Width: 10
- Length: 120

Predict

Actual



Stress Mises

Hollow rectangular section

- Height: 10
- Width: 15
- Thickness: 1.5
- Length: 120

Predict

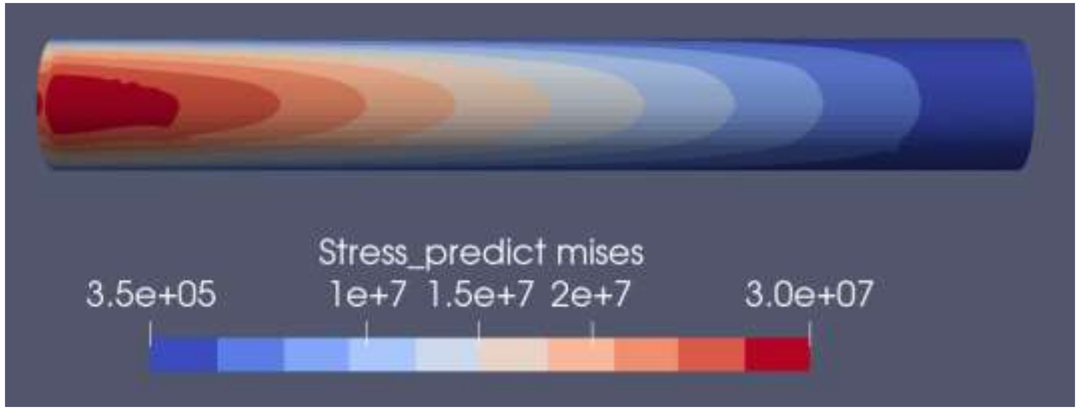
Actual

Stress Mises

Circular section

- Radius: 7.5
- Length: 110

Predict



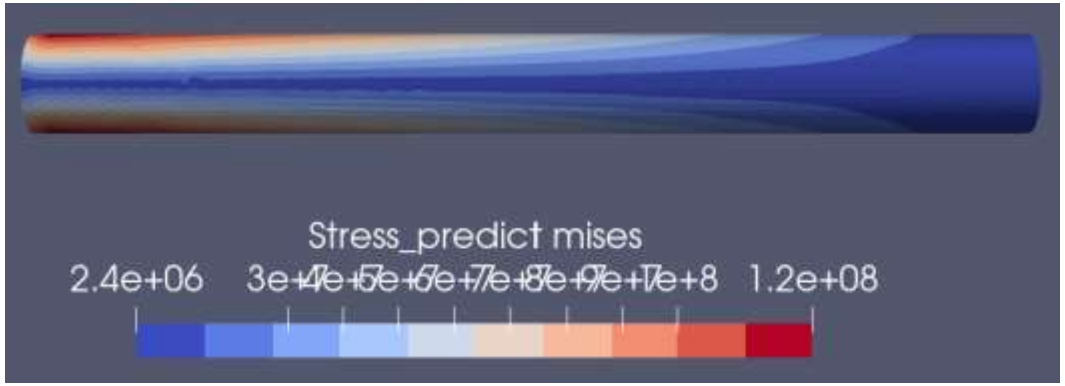
Actual

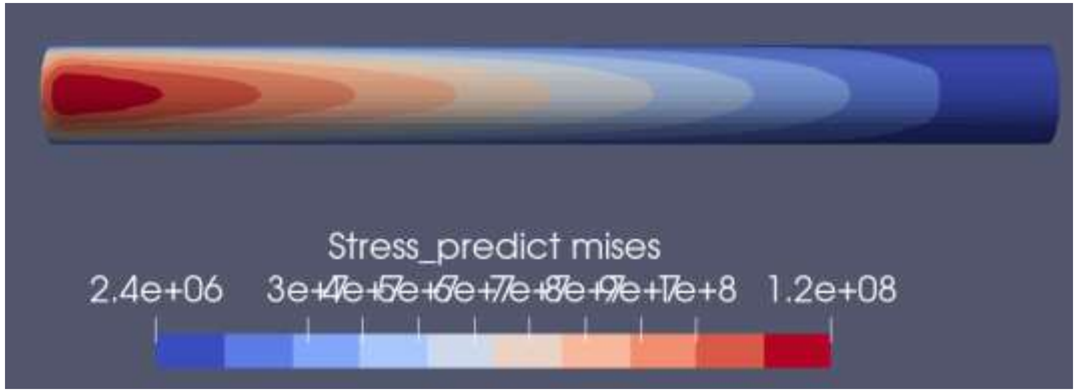
Stress Mises

Hollow circular section

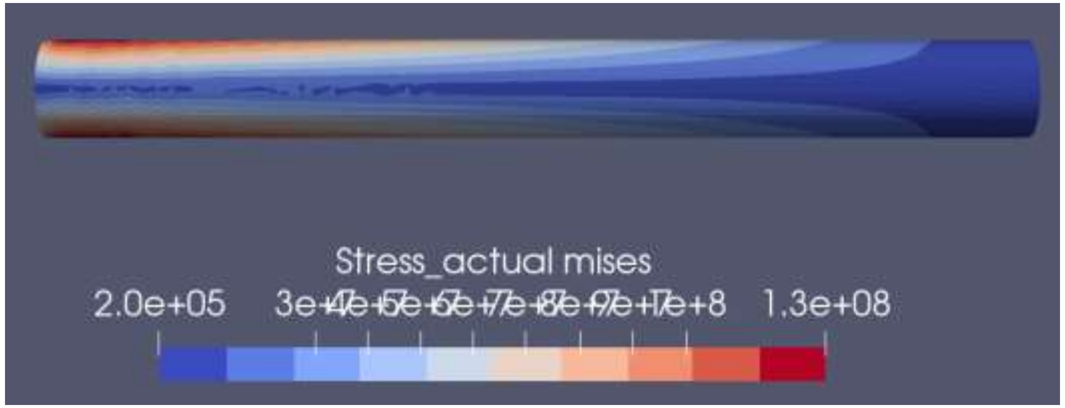
- Radius: 7.5
- Thickness: 1
- Length: 120

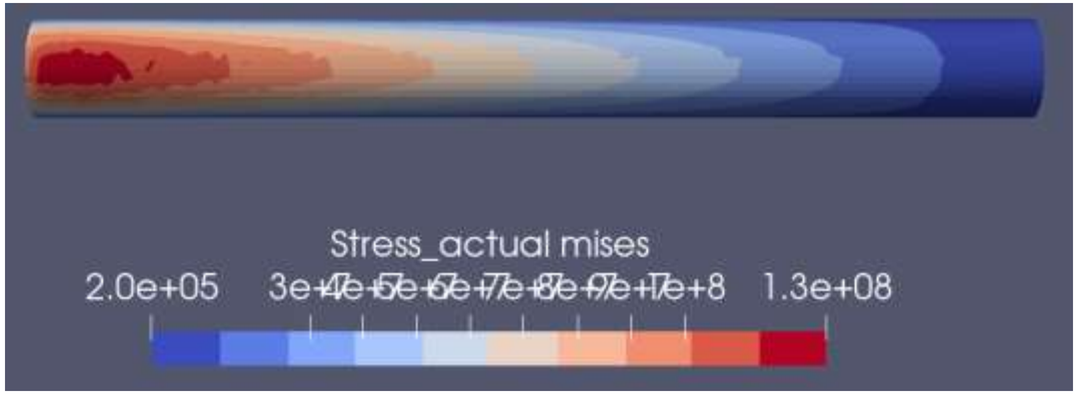
Predict





Actual





Stress Mises

I shape section

- Height: 12
- w: 12
- t1: 3
- t2: 1.5
- Length: 120

Predict

Actual

Stress prediction results (unknown model)

- The trained surrogate model is employed to validate predicted results in an unknown model characterized by geometry dimensions not included in the training.
- The predicted results are compared across the five geometries listed in the table below. There is excellent agreement with the FEM results (Actual: reference value) for the maximum Mises stress at the left end (constrained end).
- A detailed discussion of the results is provided in the Mises Stress Contour Diagram Comparison (page 43 and following).

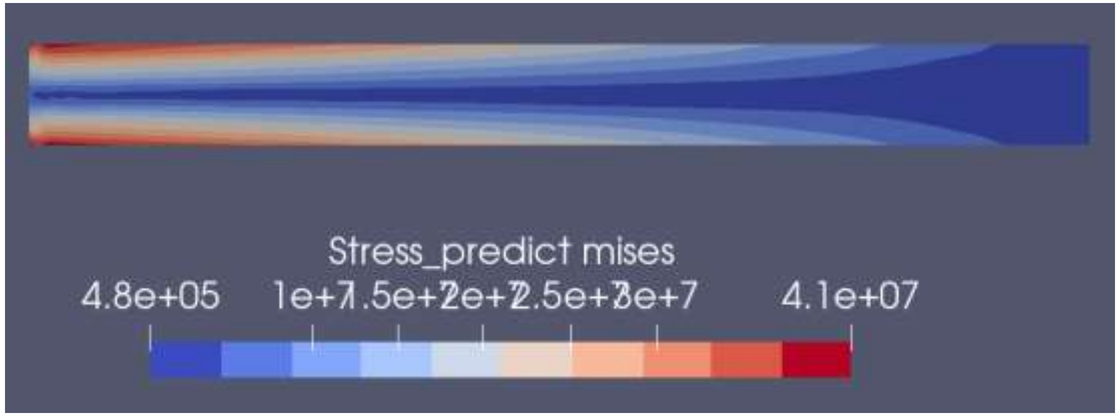
Cross-section	Mises stress (ref.)	Mises stress (predicted)	Error	Note
Rectangular	4.20E+07	4.10E+07	0.02	Height: 11,Width: 13,Length: 115
Hollow rectangular	1.40E+08	1.50E+08	0.07	Height: 10,Width: 5,Thickness: 1,Length: 90
Circular	4.90E+07	4.70E+07	0.04	Radius: 6.5,Length: 115
Hollow circular	3.60E+07	3.40E+07	0.06	Radius: 8,Thickness: 1.5,Length: 90
I shape	3.30E+07	3.70E+07	0.12	Height: 20,w: 12,t1: 1.5,t2: 1.5,Length: 120

Stress Mises

Rectangular section

- Height: 11
- Width: 13
- Length: 115

Predict



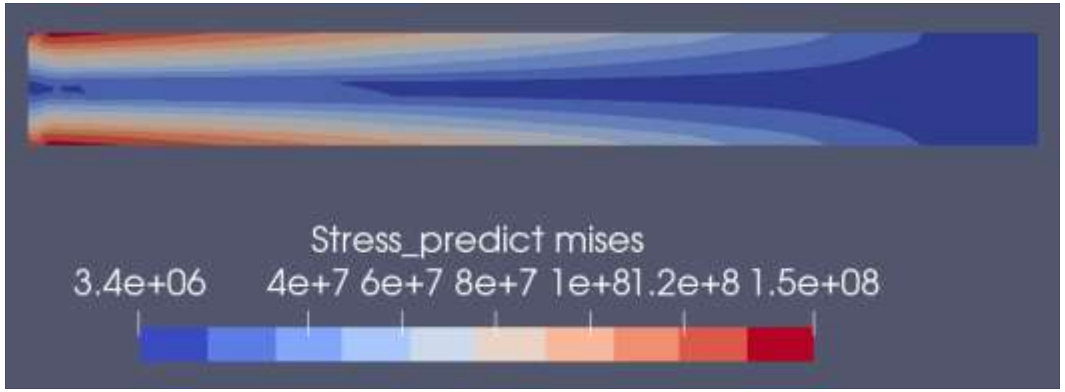
Actual

Stress Mises

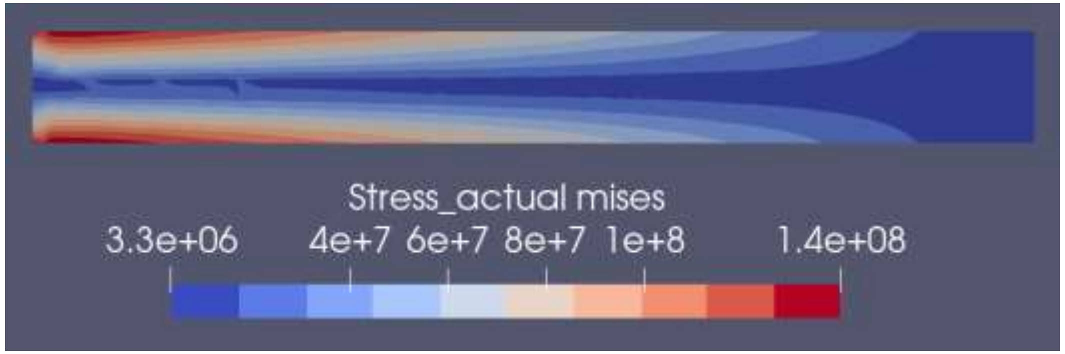
Hollow rectangular section

- Height: 10
- Width: 5
- Thickness: 1
- Length: 90

Predict



Actual

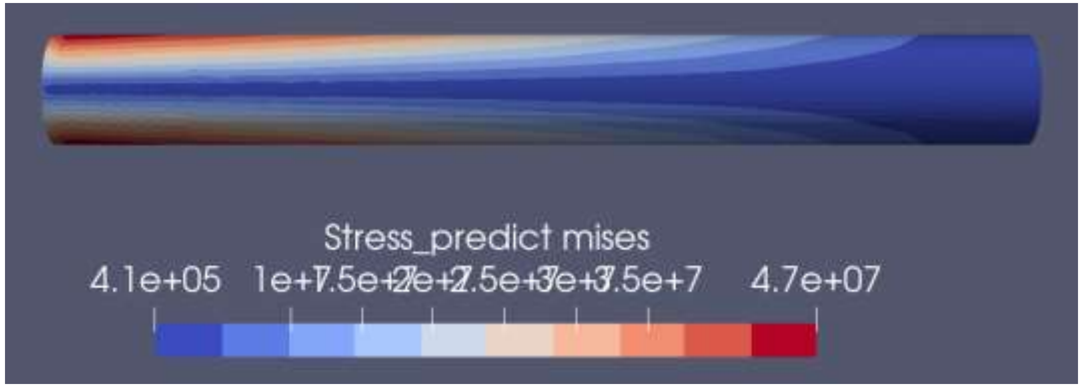


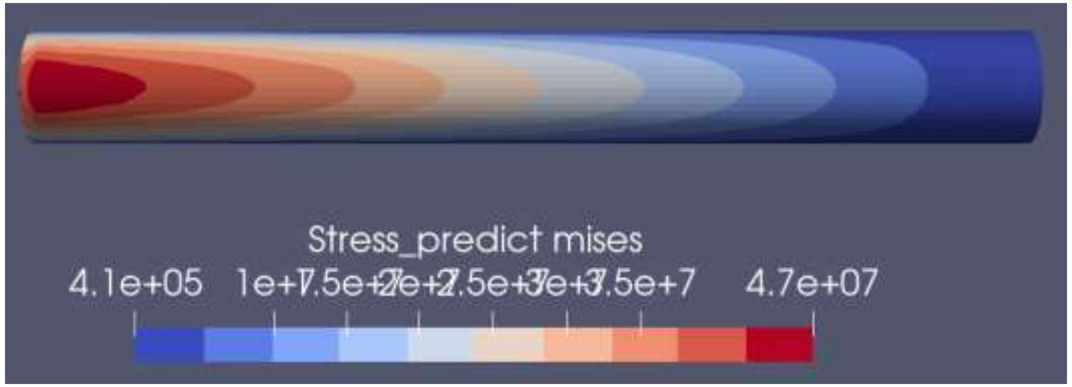
Stress Mises

Circular section

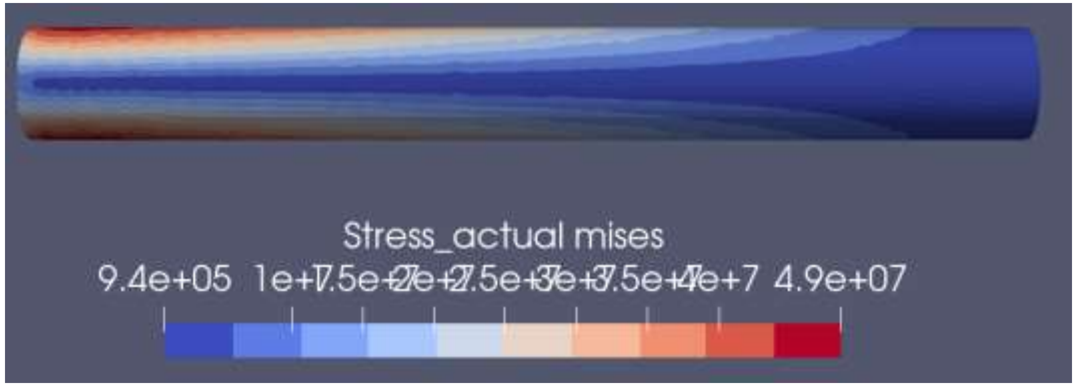
- Radius: 6.5
- Length: 115

Predict





Actual

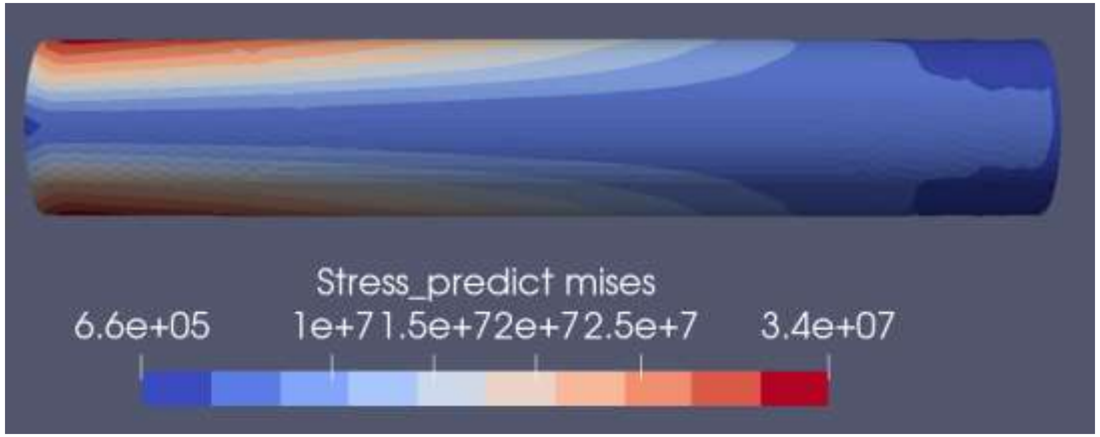


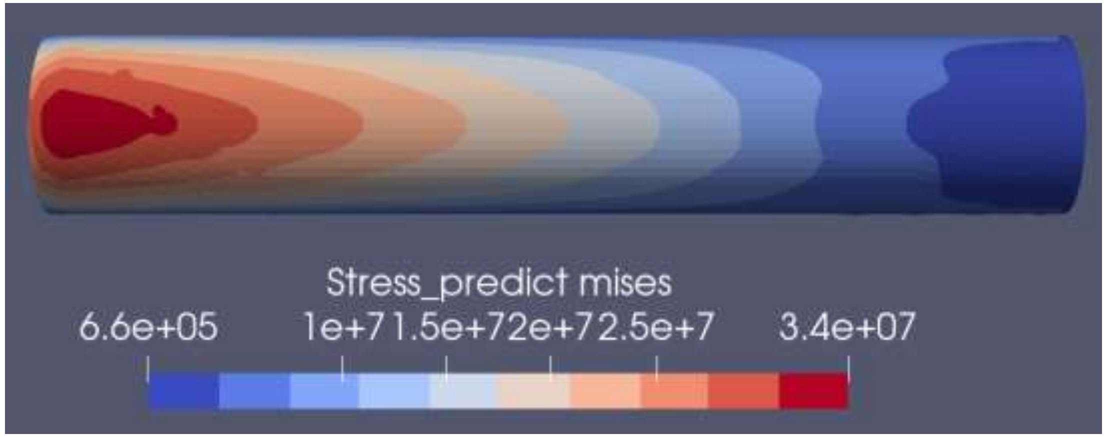
Stress Mises

Hollow circular section

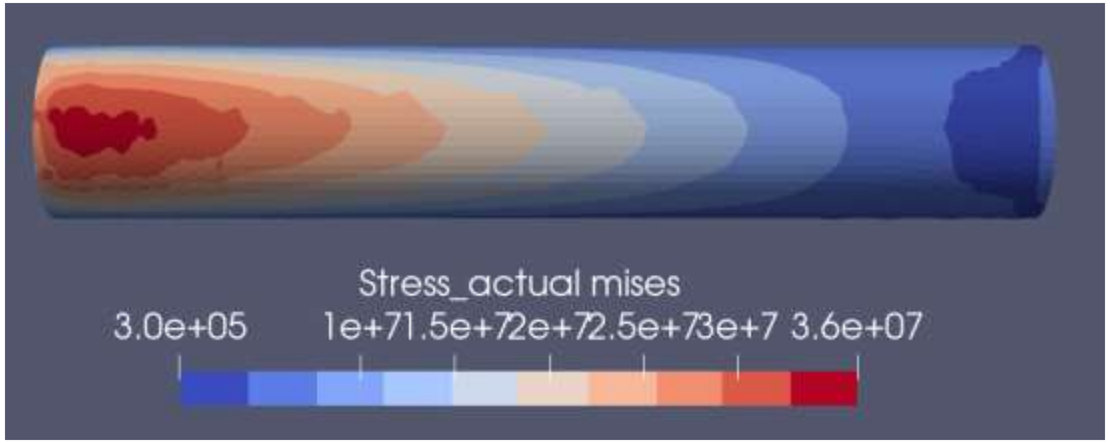
- Radius: 8
- Thickness: 1.5
- Length: 90

Predict





Actual



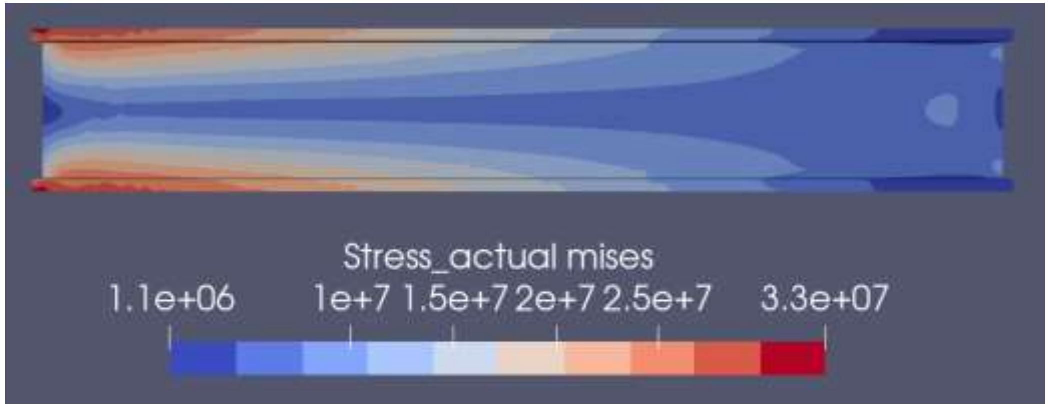
Stress Mises

I shape section

- Height: 20
- w: 12
- t1: 1.5
- t2: 1.5
- Length: 120

Predict

Actual



Conclusion

- The predicted results of the AI model demonstrated excellent agreement with the FEM results for both displacements and stresses. The stress contour plots exhibited smooth boundaries that are equal to or better than the FEM results.
- The number of training data points was 325, which is 1/100th of the data utilized in a previously created GNN surrogate model.
- Although the same conditions cannot be asserted for the PINNs, this indicates that the quantity of training data can be significantly reduced using PINNs.
- There remains room for improvement in the predictive performance for unknown data, which could be enhanced by increasing the comprehensiveness of the training data.
- This work paves the way for the application of PINNs in GCNs.

End