Elasto-Plastic Surrogate Models via Neuronal Networks

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Outline

Surrogate Modelling for Finite Elements Simulations

Finite Element Model

Dataset Generation

Recurrent Neural Networks

Neural Network

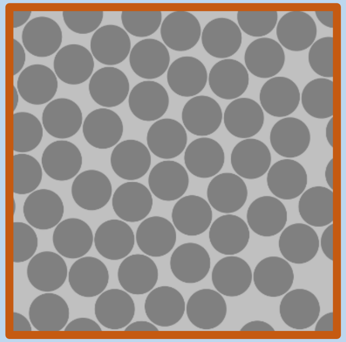
Results

Conclusions

Surrogate Modelling for FE Simualtions

Meso/Macro-Scale

Micro-Scale Simulations



Homogenization

Constitutive Law
- Elastic
- Plastic
- ...

Implementation in FE Code

Traditional Modelling

Data-Drivem Modelling

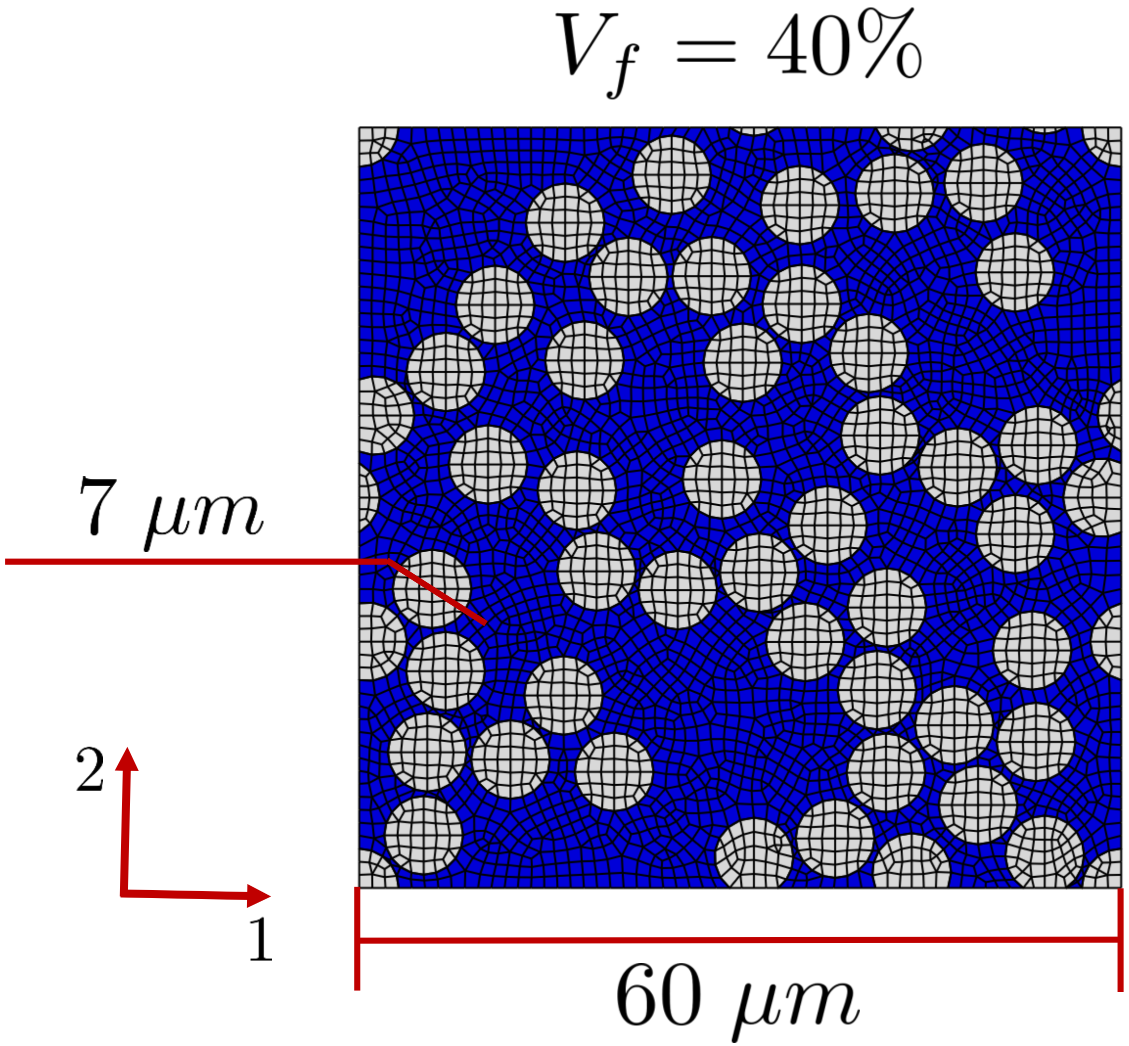
Training

Machine Learning Model

Surrogate Model

Calling from FE Code

FE Model. Representative Volume Element



Intermediate Modulus Carbon Fibres

$E_T[GPa]$	ν_T
13.00	0.40

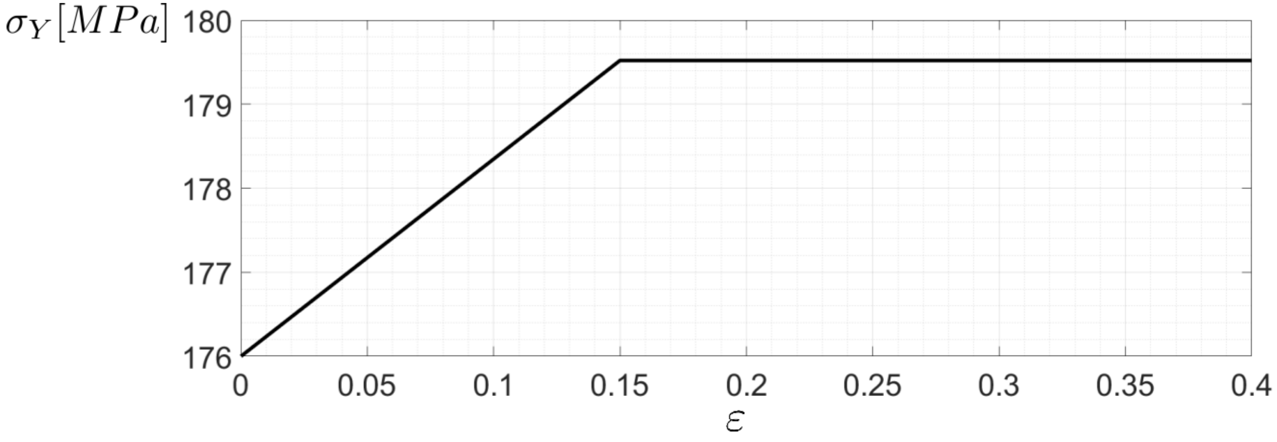
Transversally Isotropic

Perfect Interface

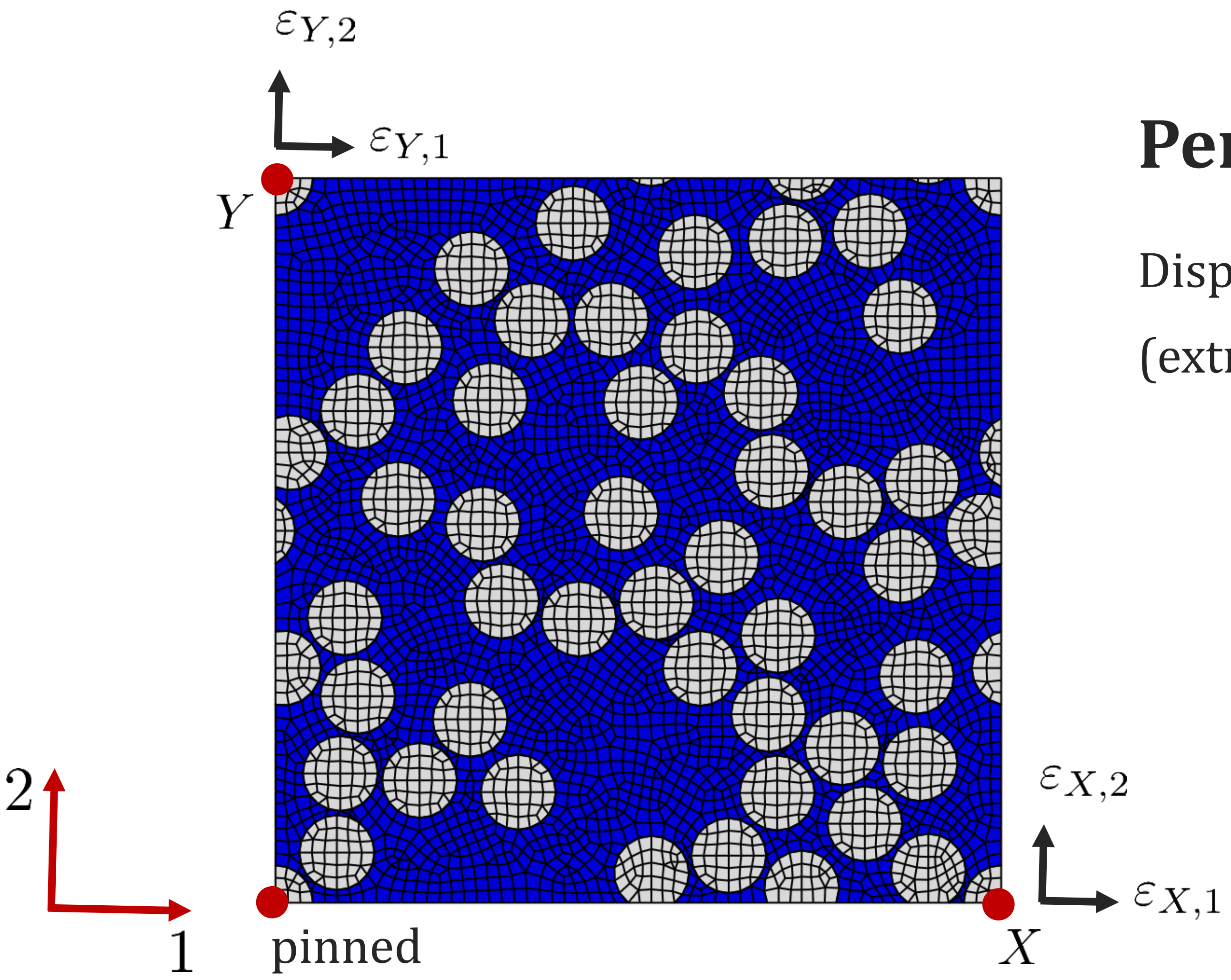
Epoxy Resin

$E[GPa]$	ν
5.07	0.35

Isotropic



FE Model. Boundary Conditions



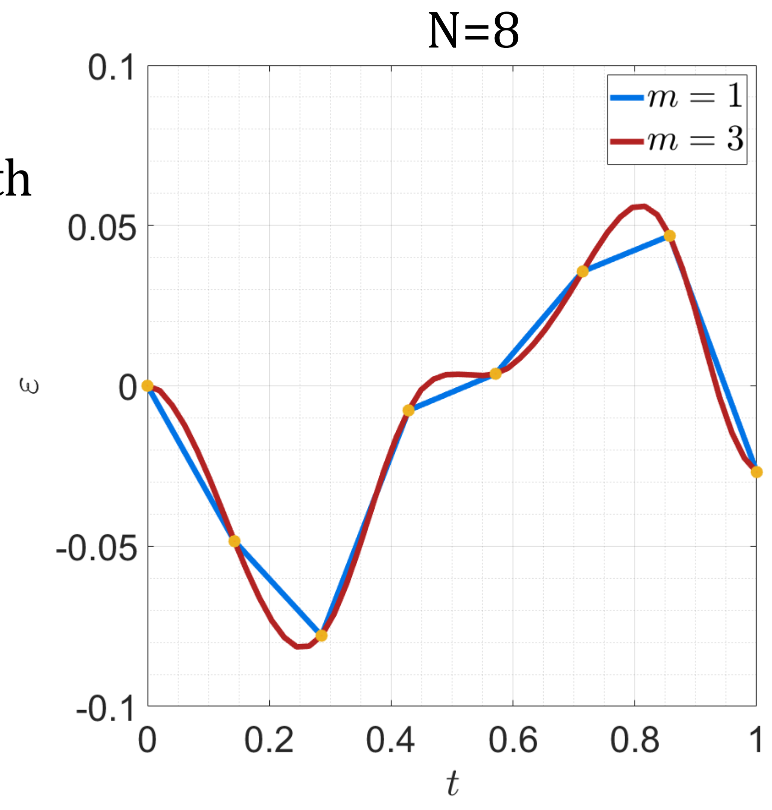
Periodic Boundary Conditions

Displacement needs to be imposed in two nodes (extra node for pinning)

Dataset Generation. Generation of strain history paths

Path connecting points in a 3D strain space:

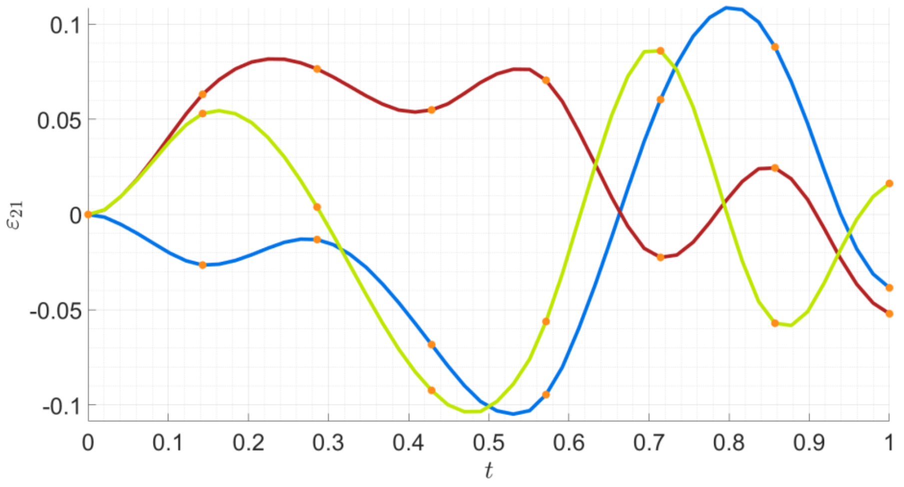
- A big set of random points is generated using Latin hypercube for ensuring a good spanning of the full strain space.
- A subset of N points is chosen from the set of points.
- The path is generated as an m-Spline connecting the subset.
- Between each of the N points, the number of points for the interpolating curve, N_{int}, is chosen in order to control the total length of the path.



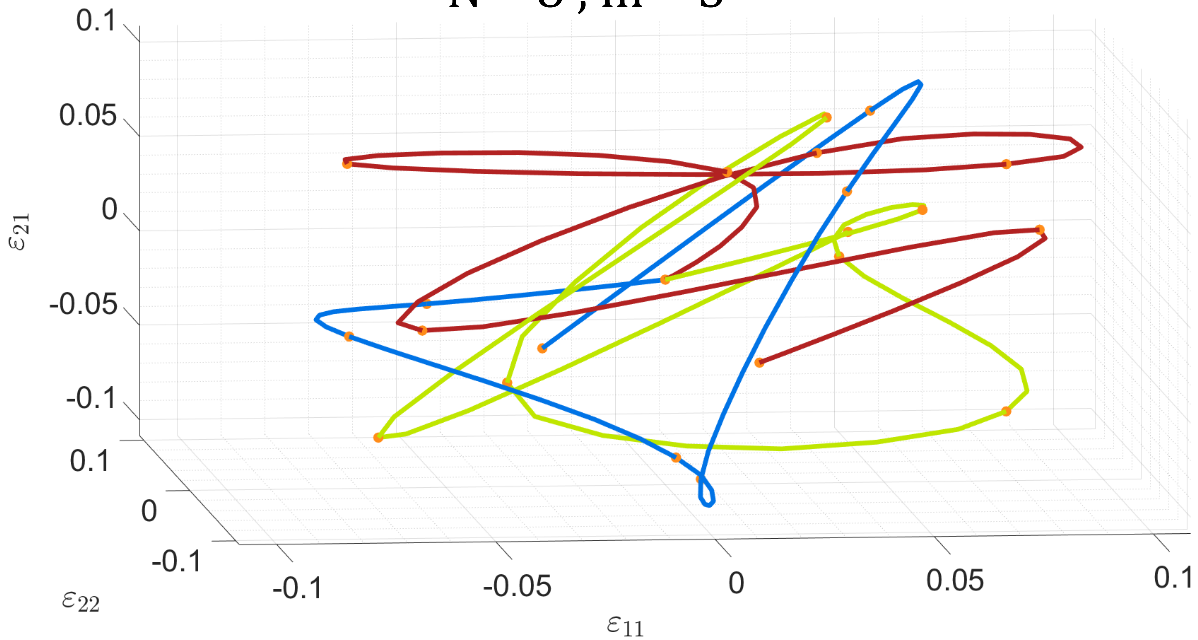
Abaqus Software is used (Implicit Solver):

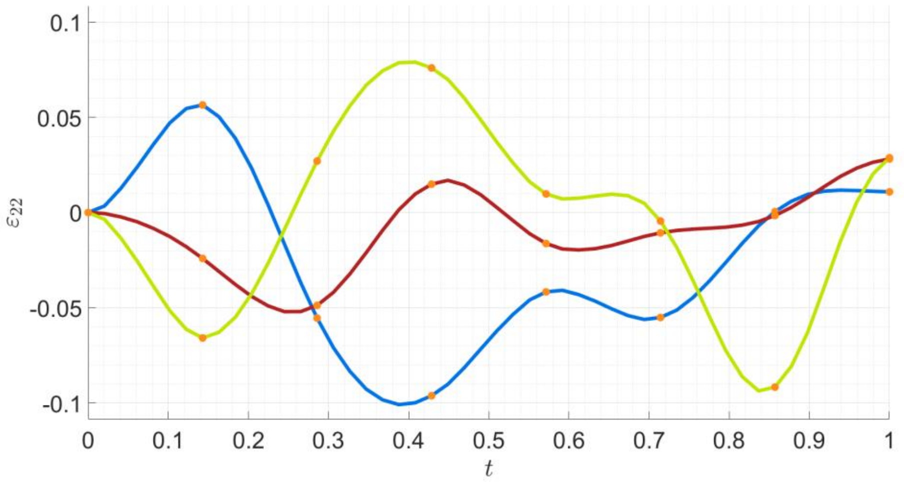
- Strain history is simulated by imposing displacement of master nodes.
- All the paths span a fixed time in simulation : $t \in [0, 1]$
- Once finished the simulation, the output file is post-processed in order to get the stress history.
- The full strain-stress dataset is stored.
- Time of each (simulation + post-process) : $\sim 60 - 100\text{sec}$ (3 cores, 2.5 GHz)

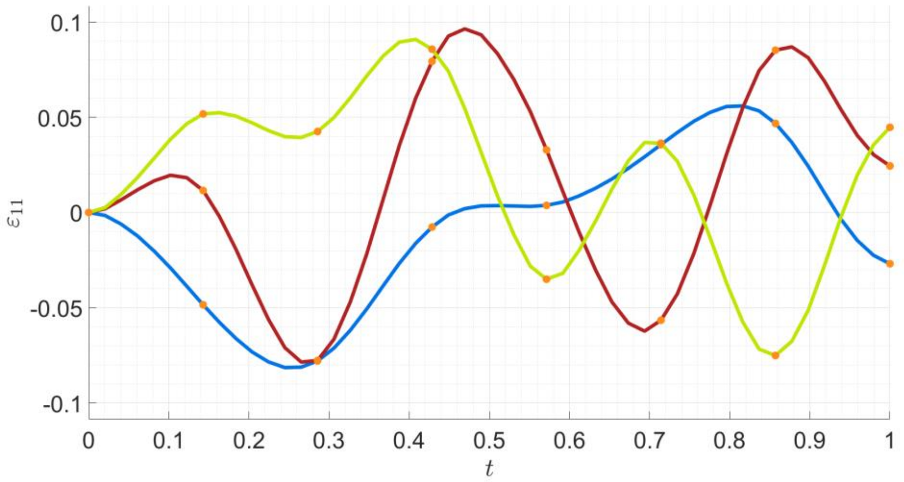
Dataset Generation. Generation of strain history paths



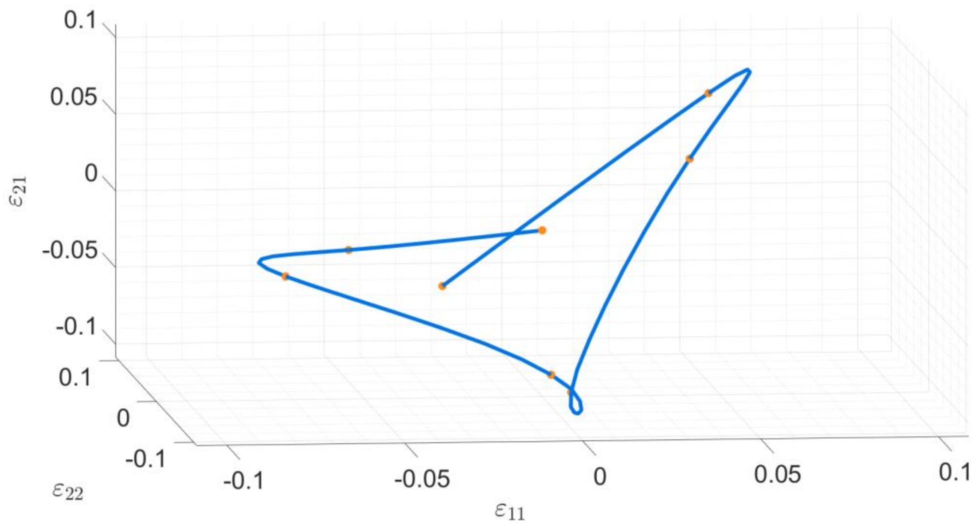
N = 8 , m = 3

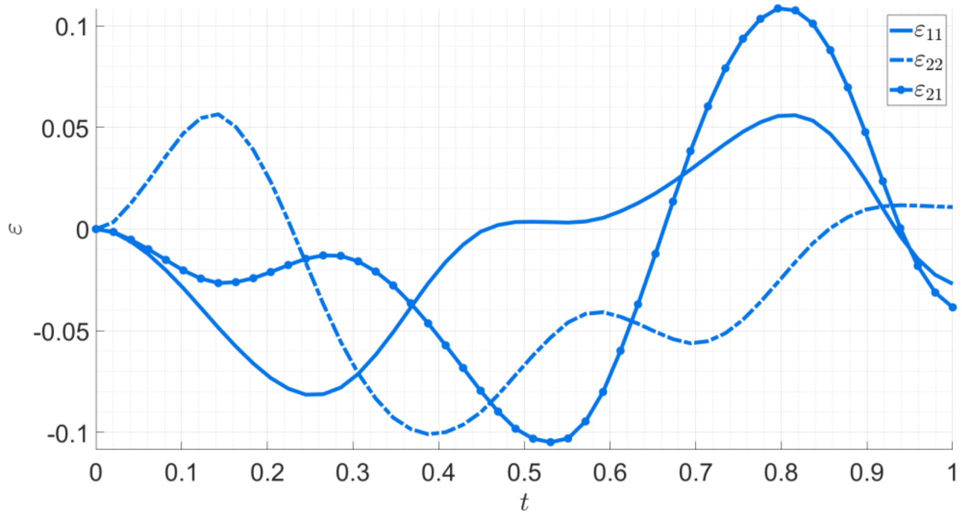


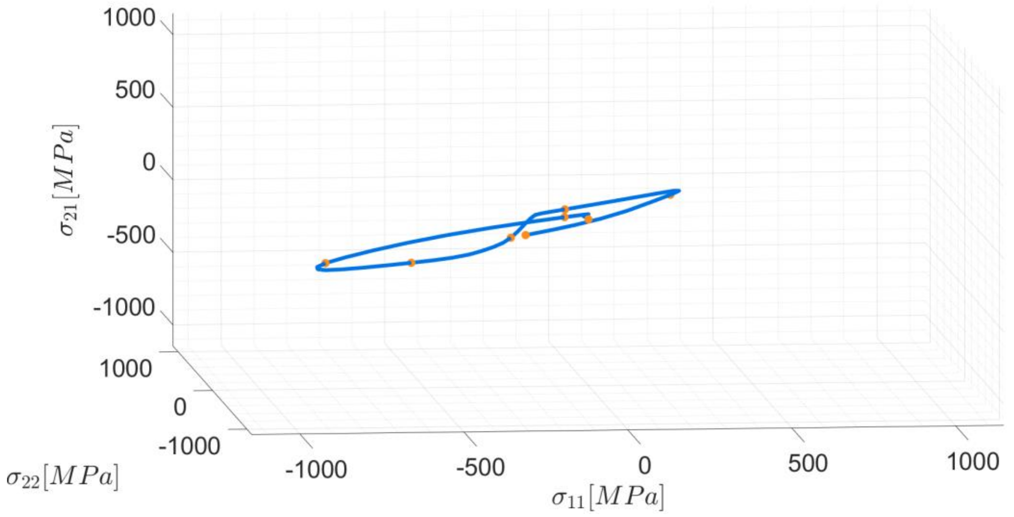


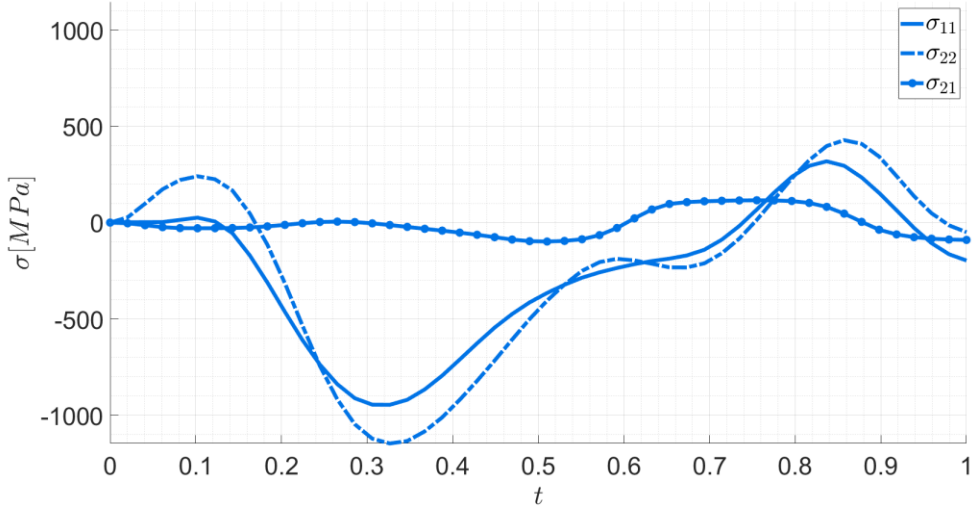


Dataset Generation. RVE's Mechanical Behaviour

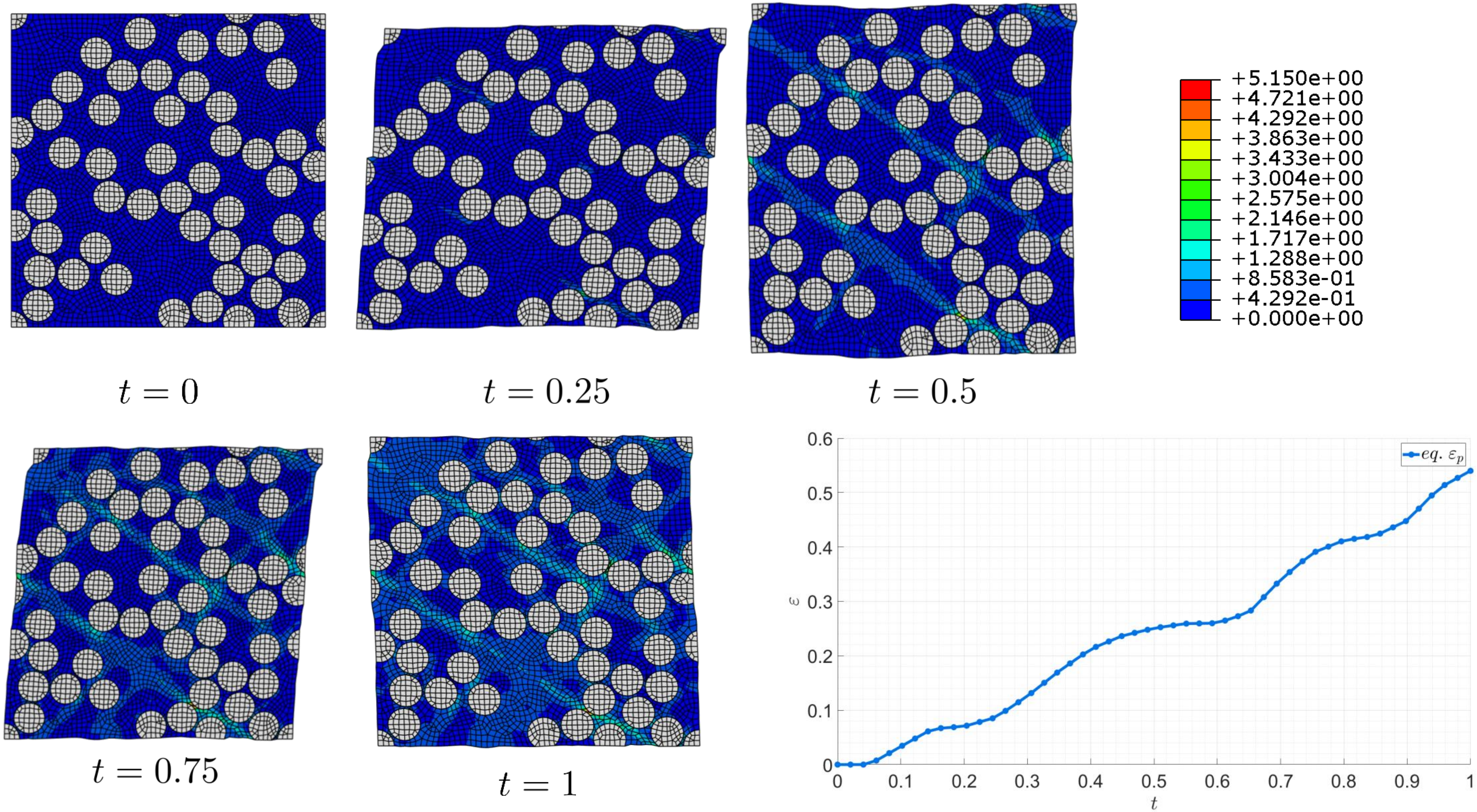




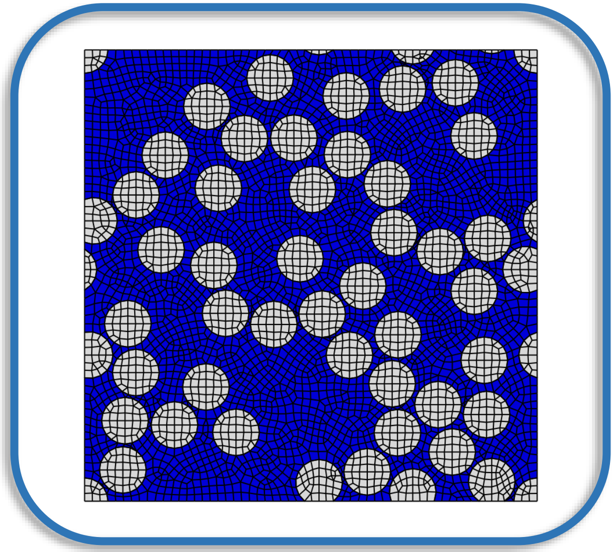


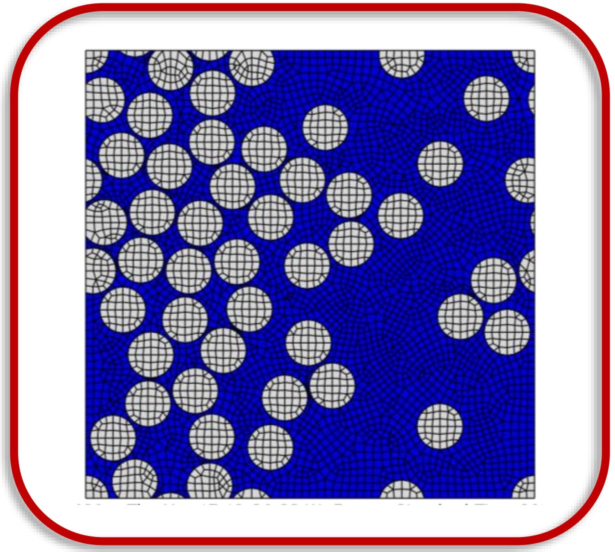


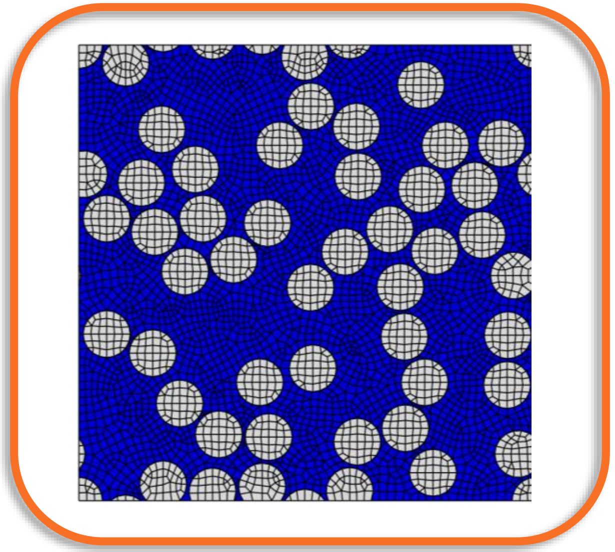
Dataset Generation. Accumulated Plastic Strain

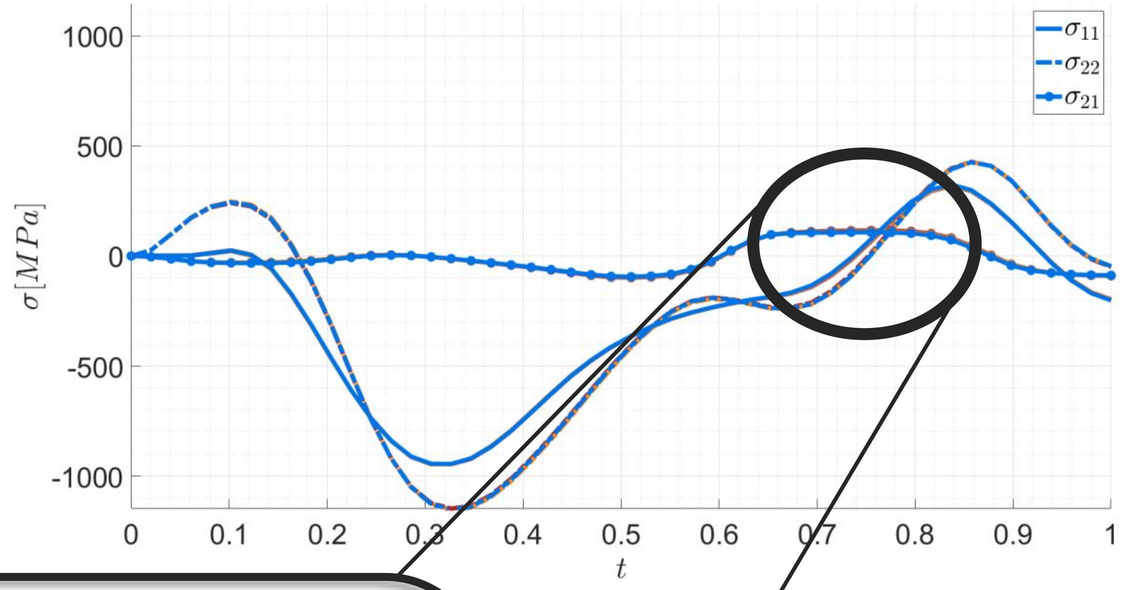


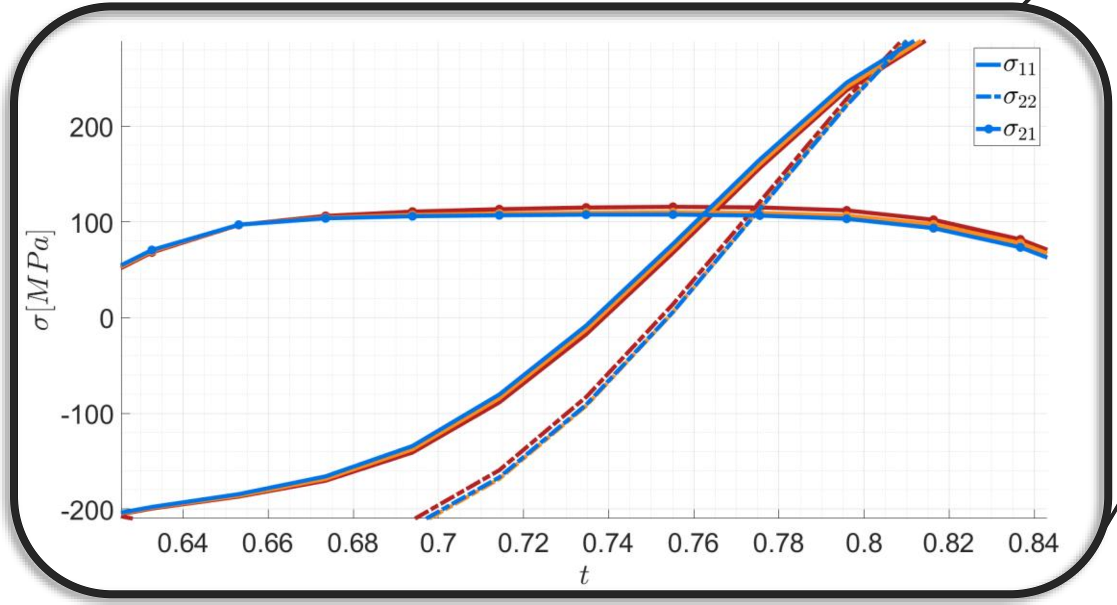
Dataset Generation. Effect of Fibre's Distribution











$$\approx 0.66\%$$

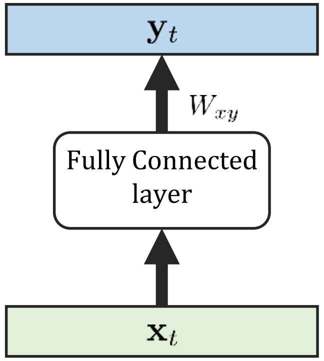
Recurrent Neural Networks

Fully Connected Neural Network

$$\mathbf{x}_t \in R^{n_x \times 1}$$

$$\mathbf{y}_t \in R^{n_y \times 1}$$

$$W_{xy} \in R^{n_x \times n_y}$$



hidden state:

$$\boxed{\mathbf{h}_t \in R^{h_{units} \times 1}}$$

$$W_{xh} \in R^{h_{units} \times n_x}$$

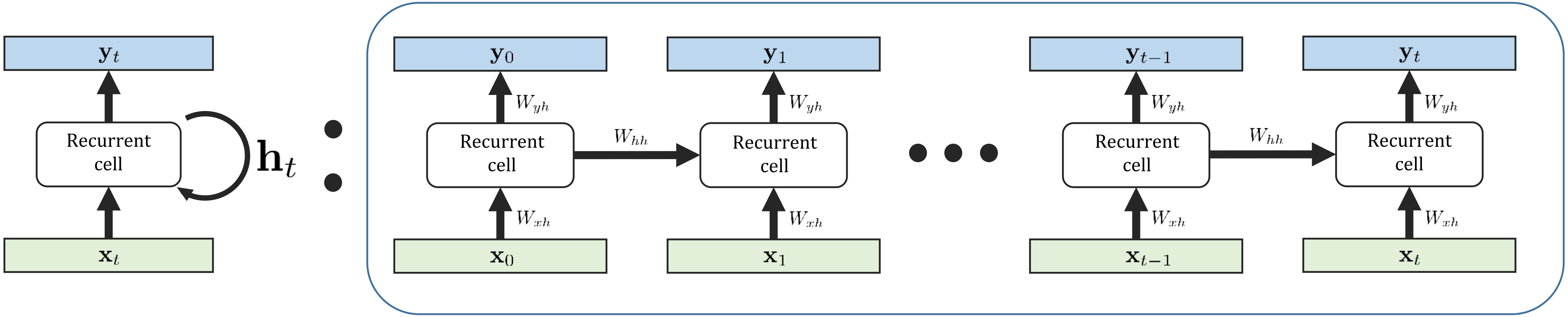
$$W_{hh} \in R^{h_{units} \times h_{units}}$$

$$W_{yh} \in R^{n_y \times h_{units}}$$

$$\mathbf{h}_t = tanh\left(W_{xh}\mathbf{x}_t + W_{hh}\mathbf{h}_{t-1}\right)$$

$$\mathbf{y}_t = W_{hy}\mathbf{h}_t$$

Initialization : $\mathbf{h}_0 = \bar{0}$



Neural Network. WorkFlow

Start Point :

- Dataset
- Chosen Neural Network Architectured compiled

Step 1: Sample paths

Step 2: Normalization

Step 3: Neural Network Training/Evaluation

Step 4: Denormalization

Step 5: Merging of Split Paths

Neural Network. Architecture

Recurrent Neural Network Arquitecture

- 1 Recurrent Cell : 100 hidden units
- Fully Connected Layer : same size than output vector

$\sim$12k parameters

Fully Connected Neural Network Arquitecture

- 5 Fully Connected Layers : 500 neurons each layer

$\sim$2M parameters

Mean Squared Error

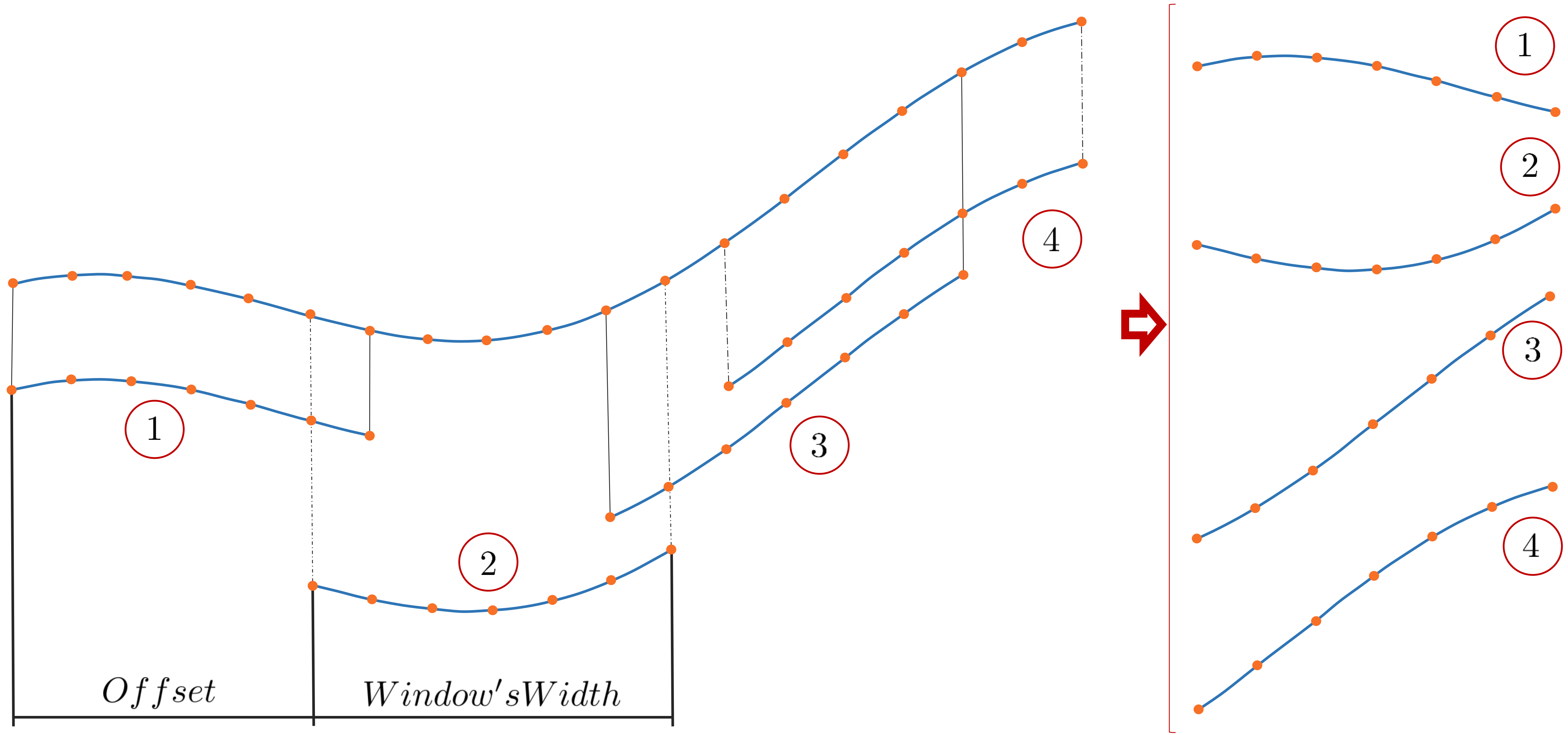
$$m.s.e = \frac{1}{N}\sum_{i=1,N}\left(\mathbf{y}_{t,i} - \bar{\mathbf{y}}_{t,i}\right)$$

Mean Absolute Error

$$m.a.e. = \frac{1}{N}\sum_{i=1,N}|\mathbf{y}_{t,i} - \bar{\mathbf{y}}_{t,i}|)$$

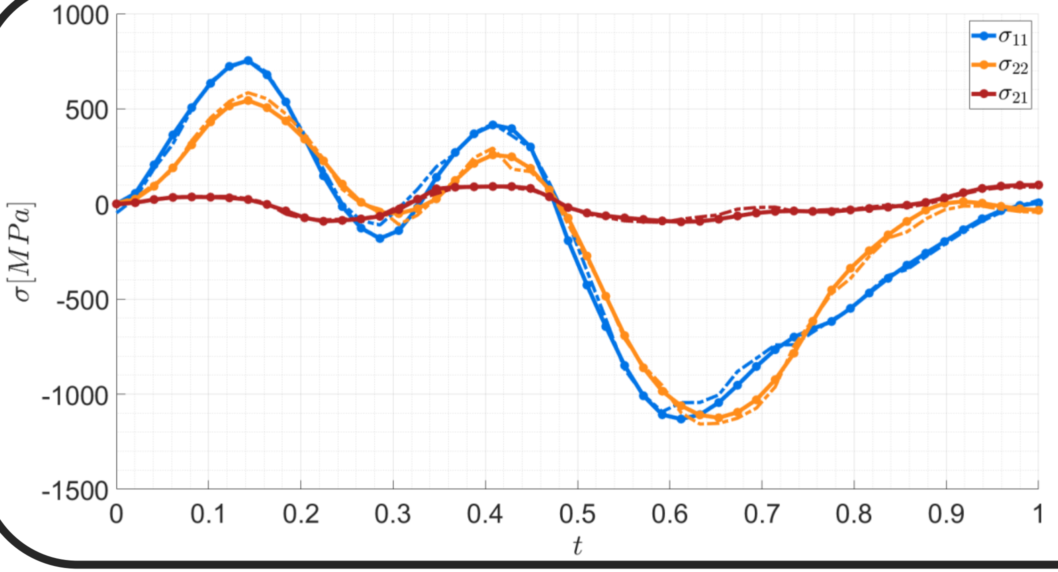
- **Loss :** m.s.e
- **Optimizer :** Adam algorithm
- **Learning Rate:** 10^{-4}

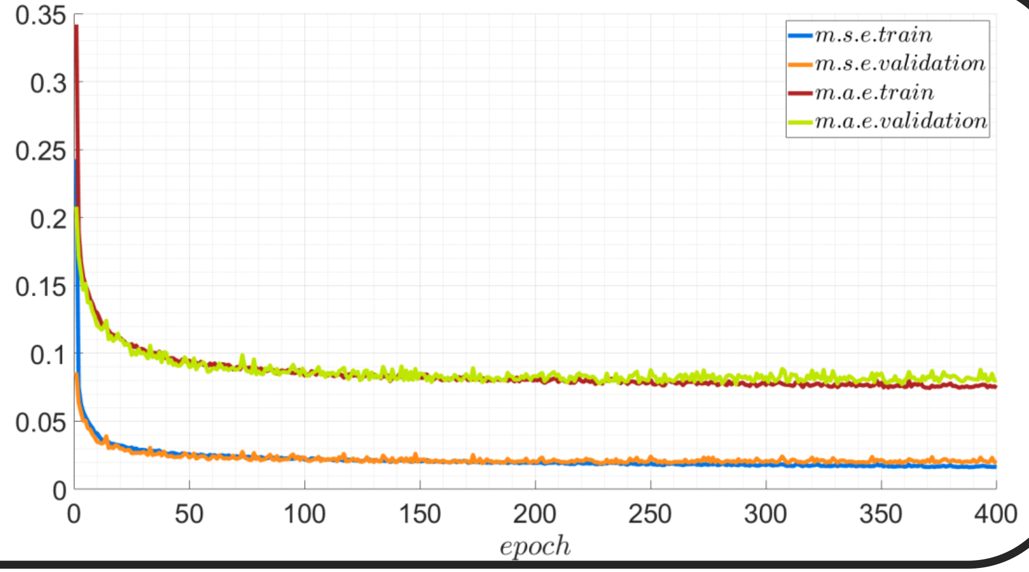
Neural Network. Sampling of Paths



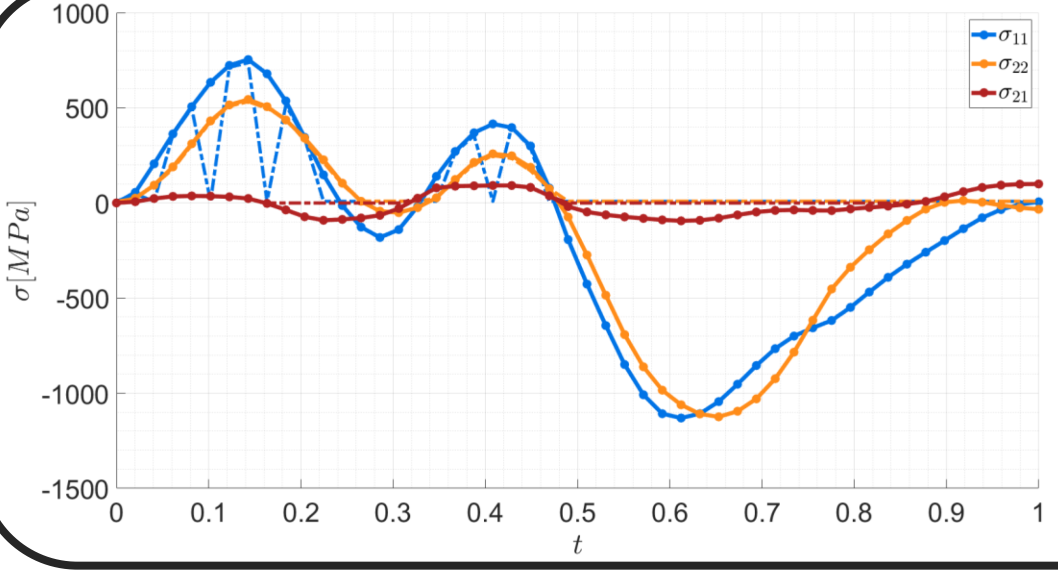
Results. Comparison FCNN vs. RNN

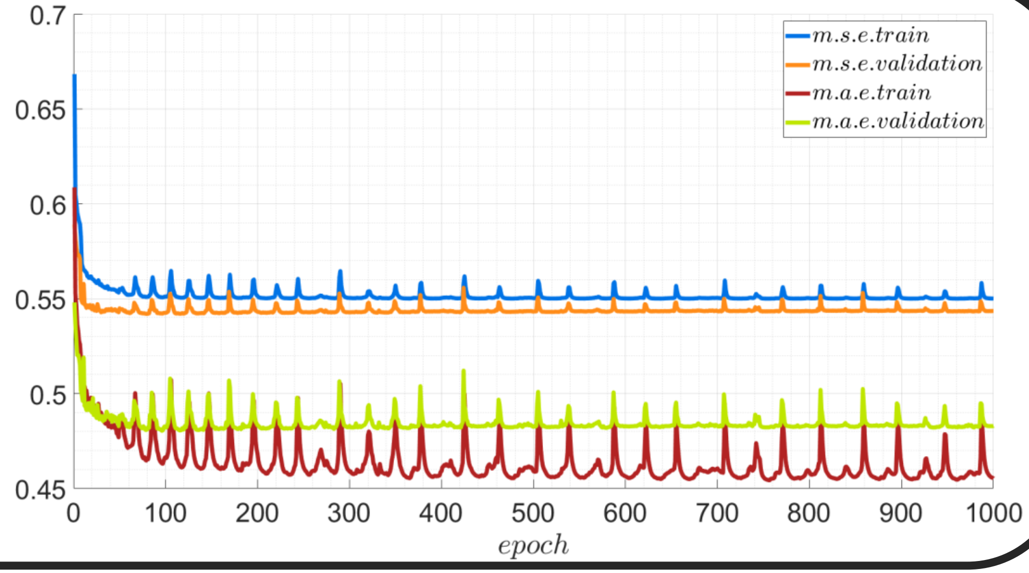
RNN





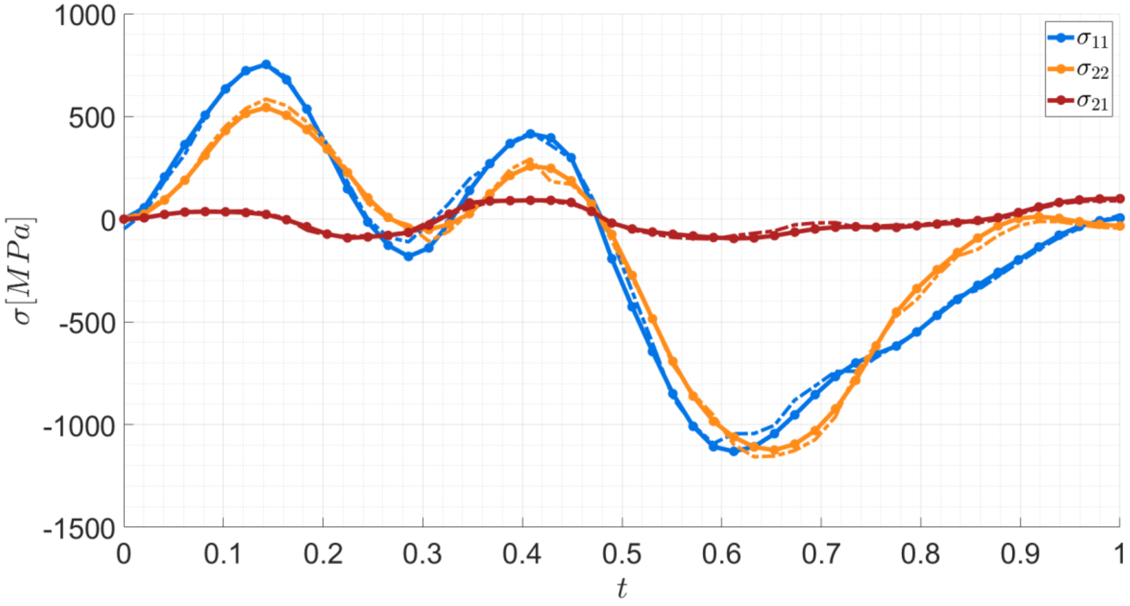
FCNN





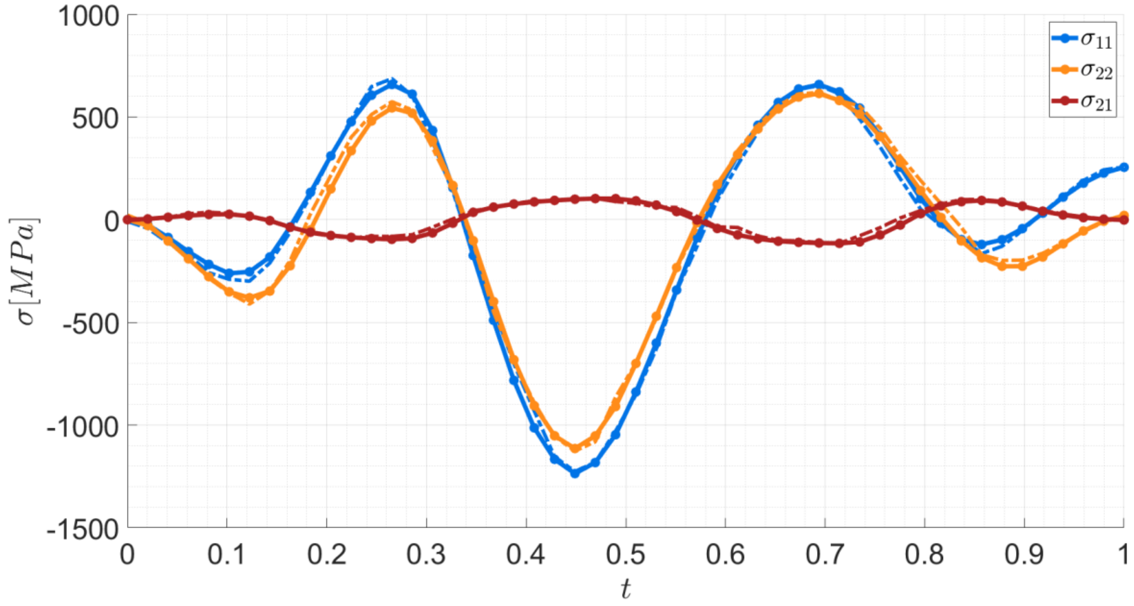
Results. Train vs. Test Sets Accuracy

Train Set



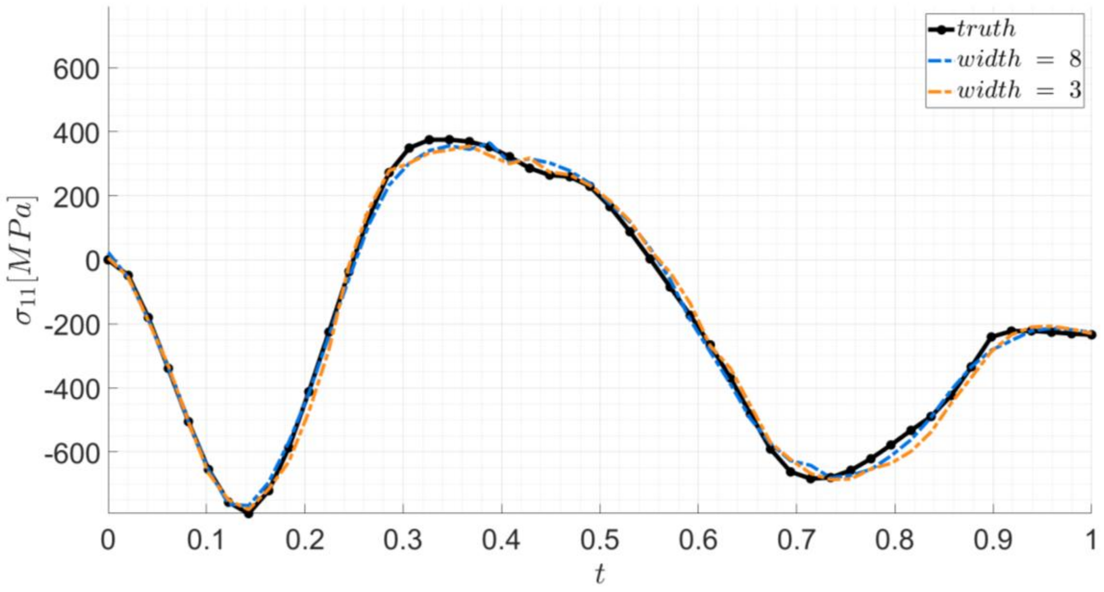
m. s. e.	m. a. e.
0.9419	13.18

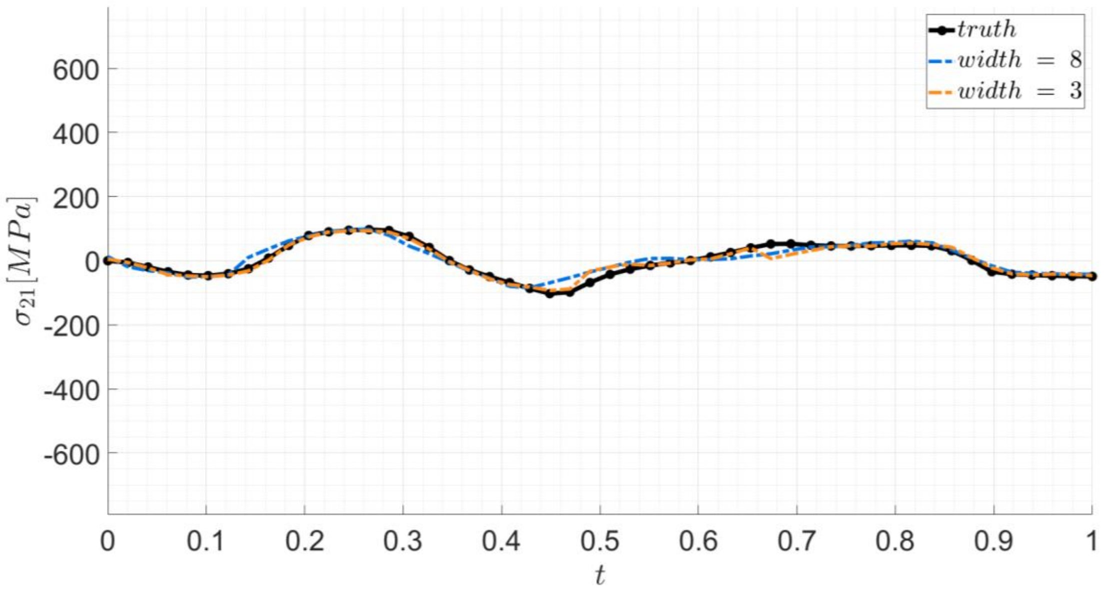
Test Set

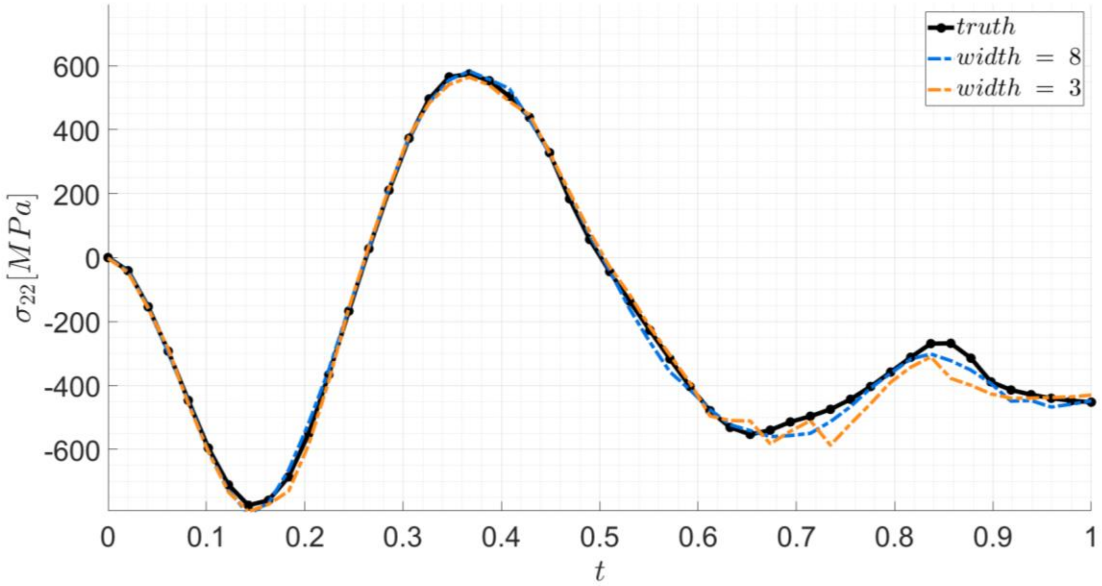


m. s. e.	m. a. e.
1.005	13.24

Results. Windows Width Effect







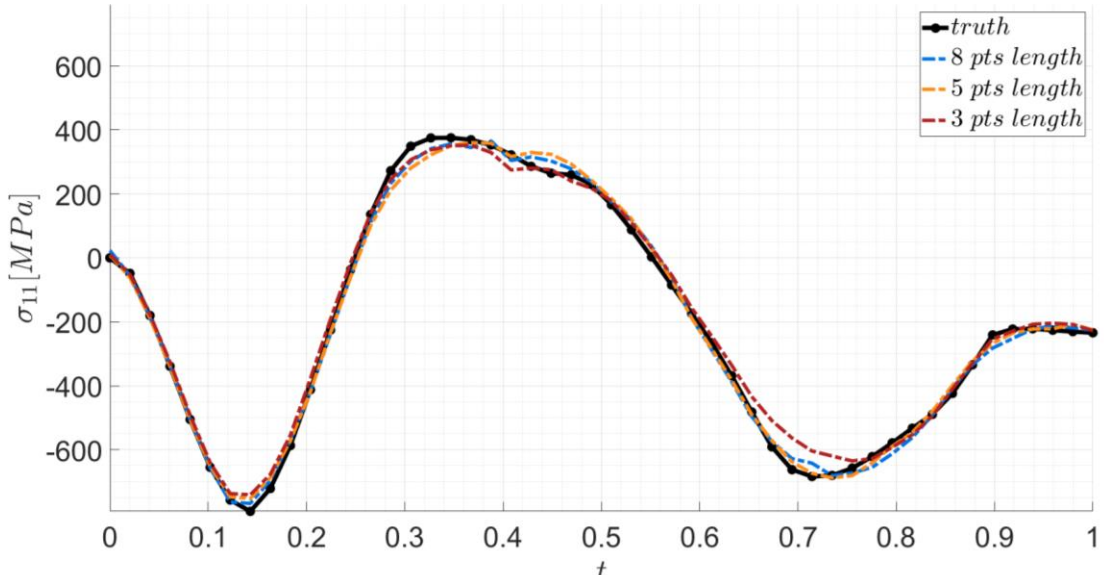
Window Size Effect:

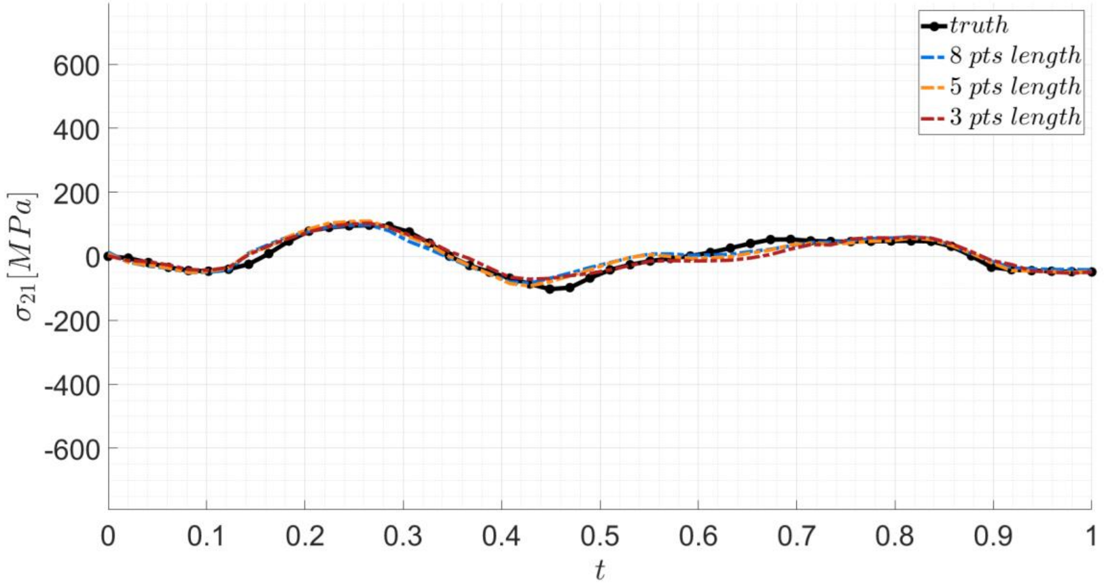
- Would be desirable to use windows as short as possible
- Evaluation on test set

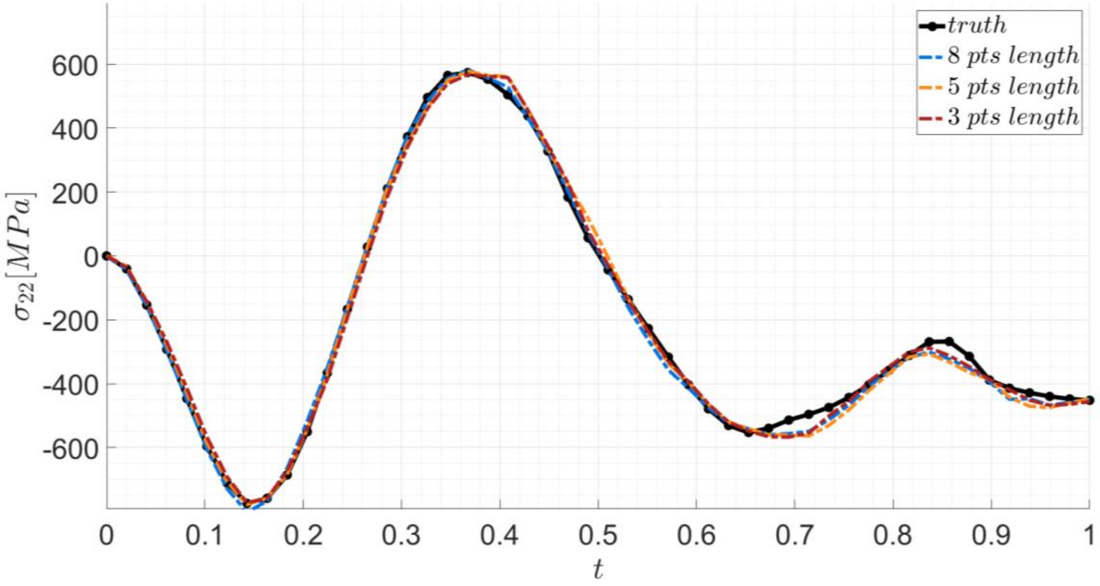
m. s. e., width = 8	m. s. e, width = 3
1.832	1.296

m. a. e., width = 8	m. a. e., width = 3
126.9	101.4

Results. Paths Length Effect







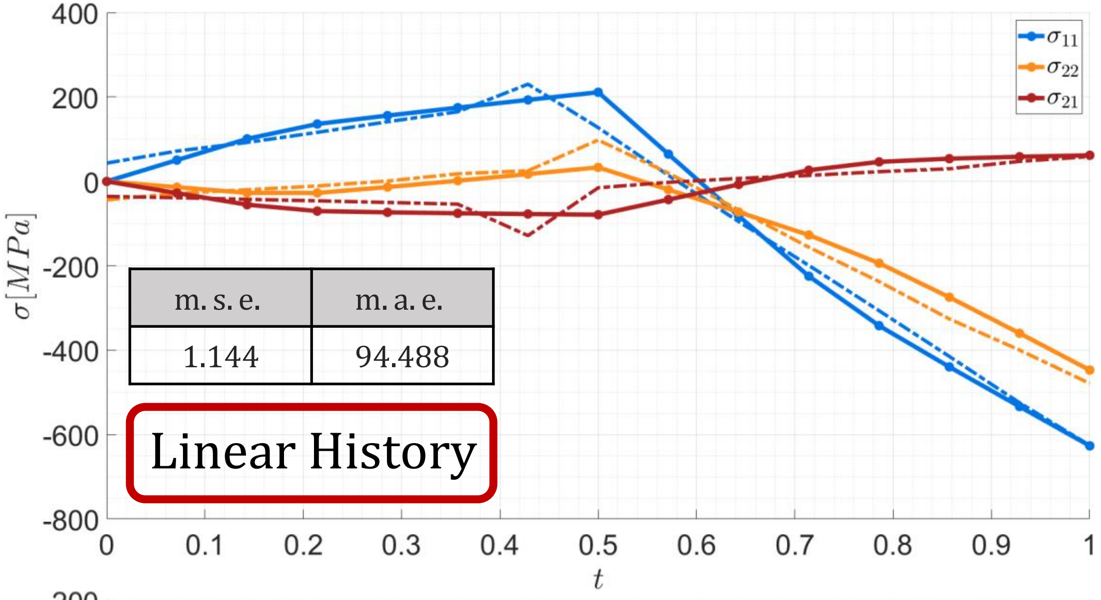
Training History Effect :

- Training with paths of 3,5 and 8 points
- Evaluation on 8 points paths database

m. s. e., 8 pts	m. s. e., 5 pts	m. s. e., 3 pts
0.9789	1.108	1.491

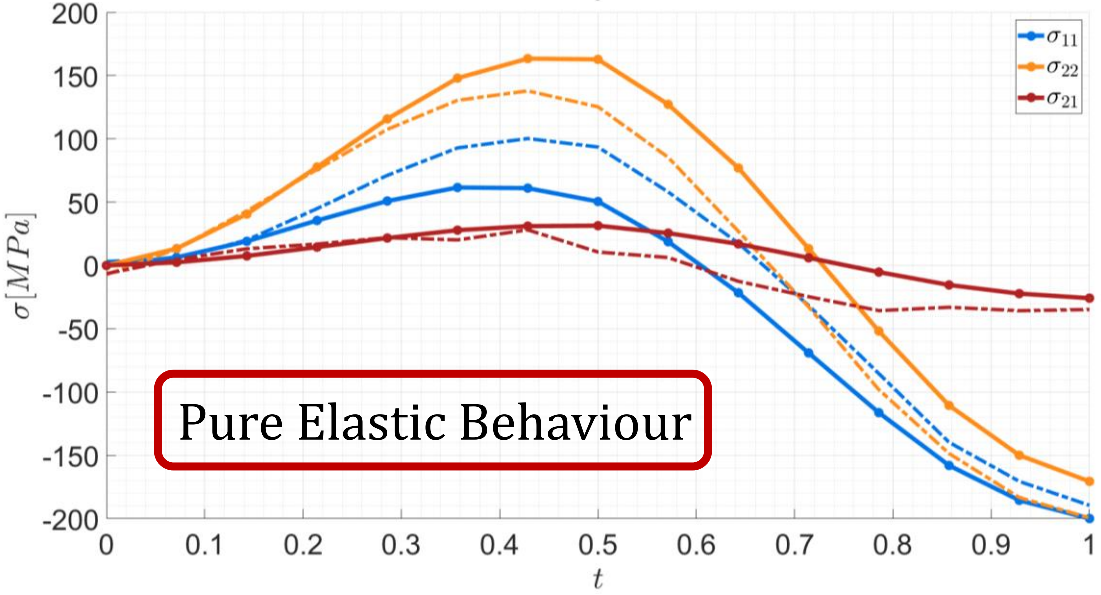
m. a. e., 8 pts	m. a. e., 5 pts	m. a. e., 3 pts
89.66	95.32	108.8

Results. Model Validation



m. s. e.	m. a. e.
1.144	94.488

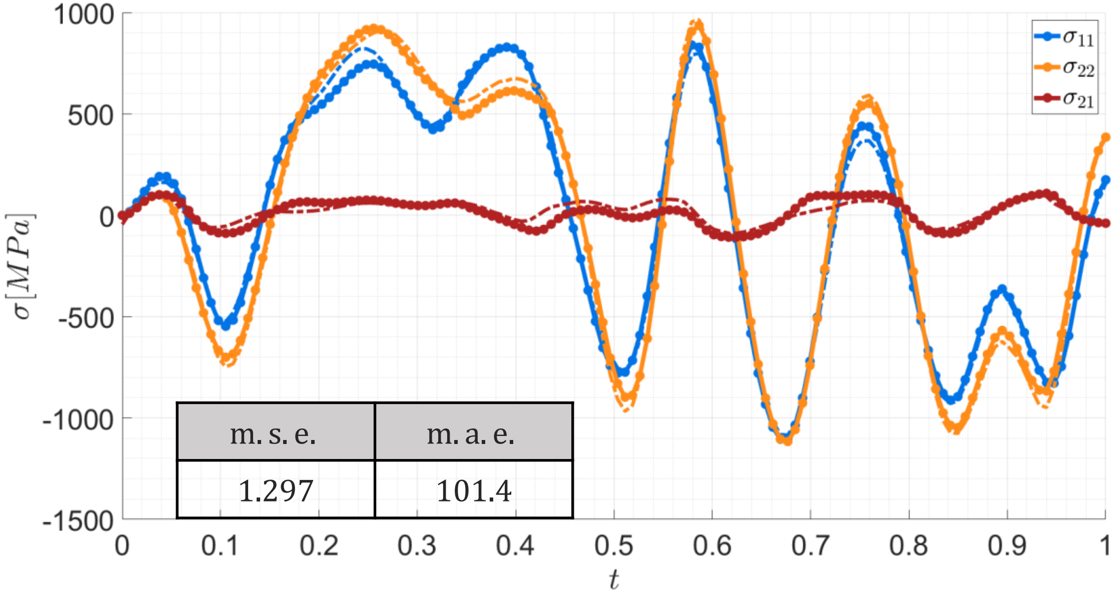
Linear History



Pure Elastic Behaviour

m. s. e.	m. a. e.
0.487	44.57

Longer History



m. s. e.	m. a. e.
1.297	101.4

Conclusions

- A methodology for training surrogate models for elasto-plastic RVEs is developed.
- The methodology is tested on a micro-scale composite material RVE with matrix plastic behaviour.
- Recurrent neural network outperform conventional fully connected networks even for very short sequences.
- The proposed method is able to reconstruct general-shape strain-stress curves beyond the plastification tresshold with aceptable accuracy.
- The proposed methodology requests of the strain history from very few previous timesteps, which makes it convenient for its use in FE analysis.

Thank you for your attention

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