University of BRISTOL
Bristol Composites Institute

Early-stage new technology Machine Learning:

Predicting the architecture of 3D textile fabrics

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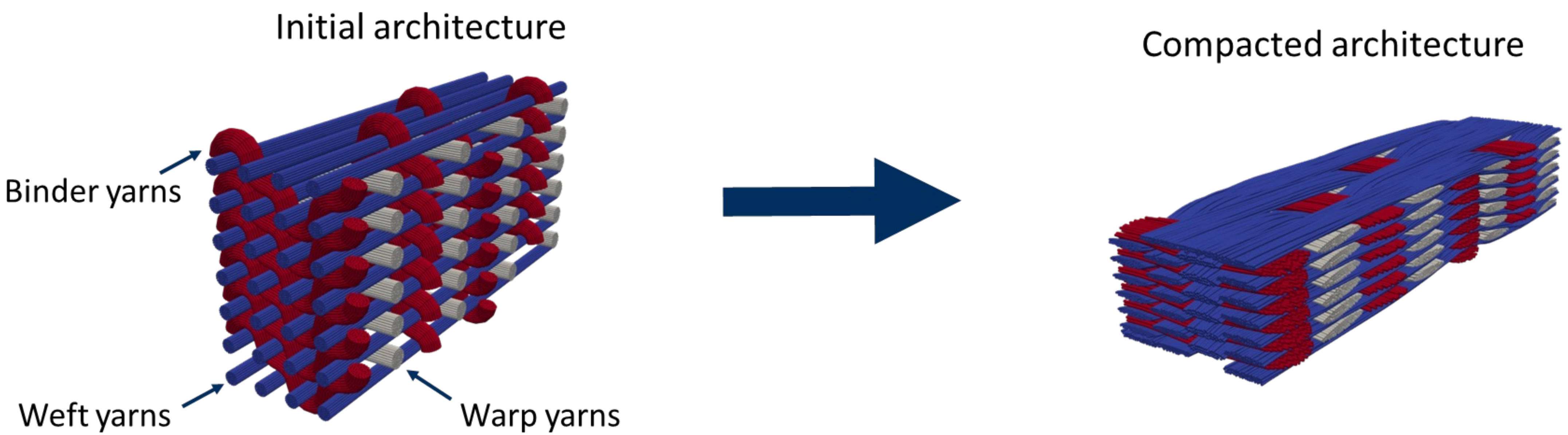
Fabrics weaving

- Weaving is one of the most common techniques for manufacturing of textile preforms.

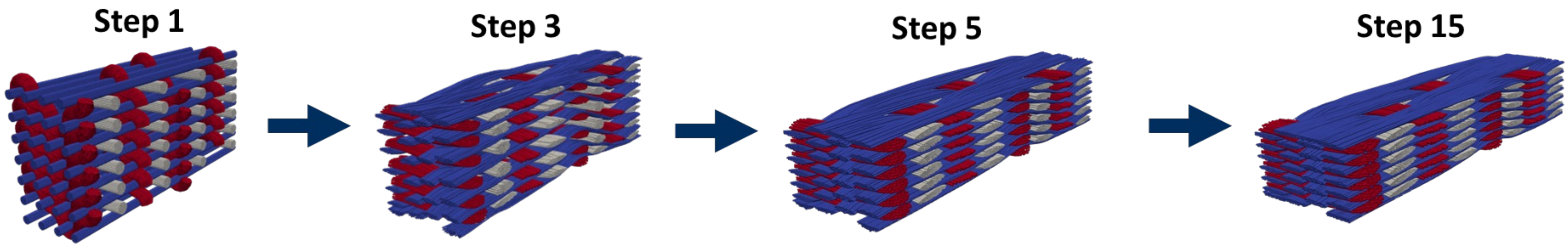


- Determining the mechanical properties of woven preforms is performed experimentally.
- It is important to be able to predict the mechanical properties of the woven fabric based on its initial geometry and architecture

Multi filament simulation

SimTex is a kinematic multi-filament solver used for the prediction of the internal architecture

Weaving simulations are performed within a number of consecutive intermediate timesteps.



[1] Bassam El Said, Steven Green, Stephen R. Hallett, *Kinematic modelling of 3D woven fabric deformation for structural scale features*, Composites: Part A, 2014, https://doi.org/10.1016/j.compositesa.2013.11.006.

Multi filament simulation

The obtained compacted kinematic model can be further translated into FE model

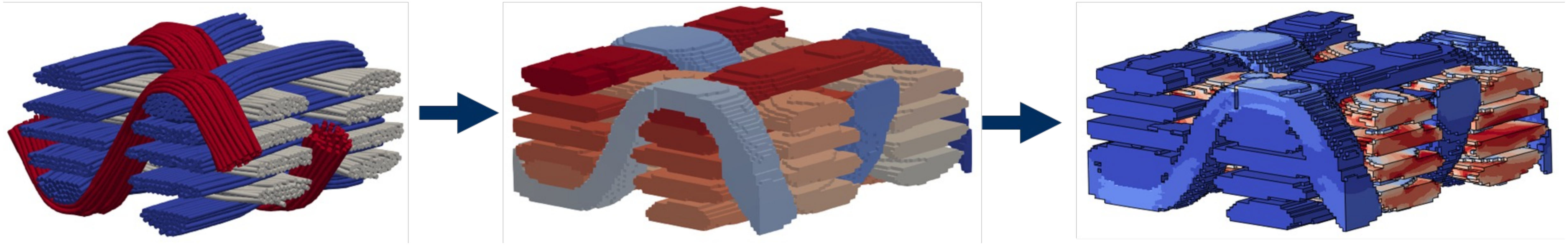
- The model is converted into a structured mesh grid (voxelised model)
- Voxelised model is converted into FE model
- This procedure can be applied to any intermediate state of the solution, not only to final geometry

Kinematic model

Voxel model

Each voxel stores data on
Fibre orientation and Fibre volume fraction

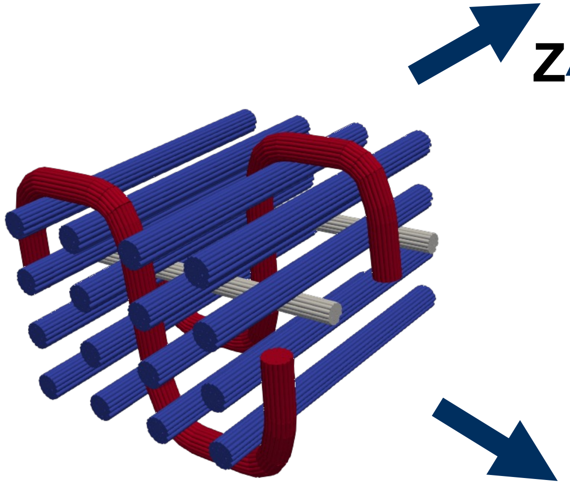
FE model



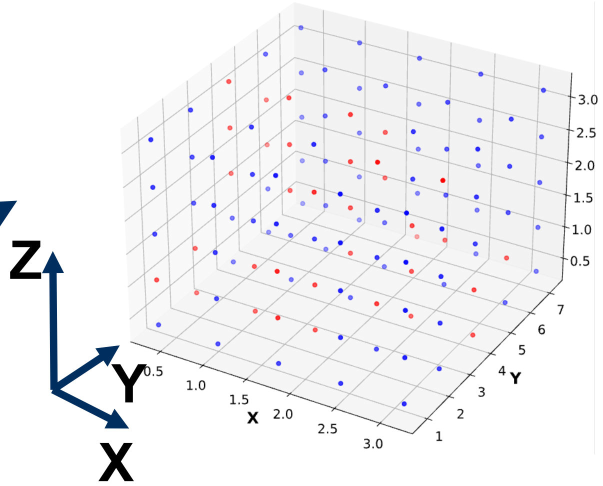
Voxel model

The density of a voxel model does not depend on the kinematic solution and can be adjusted

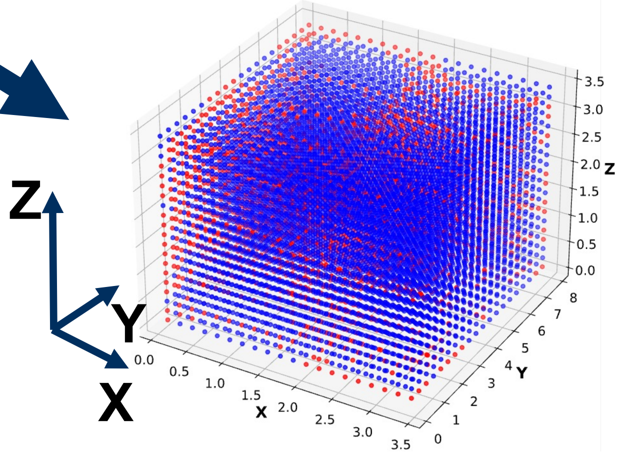
Red voxels – matrix; Blue voxels - fibres



Sparse model

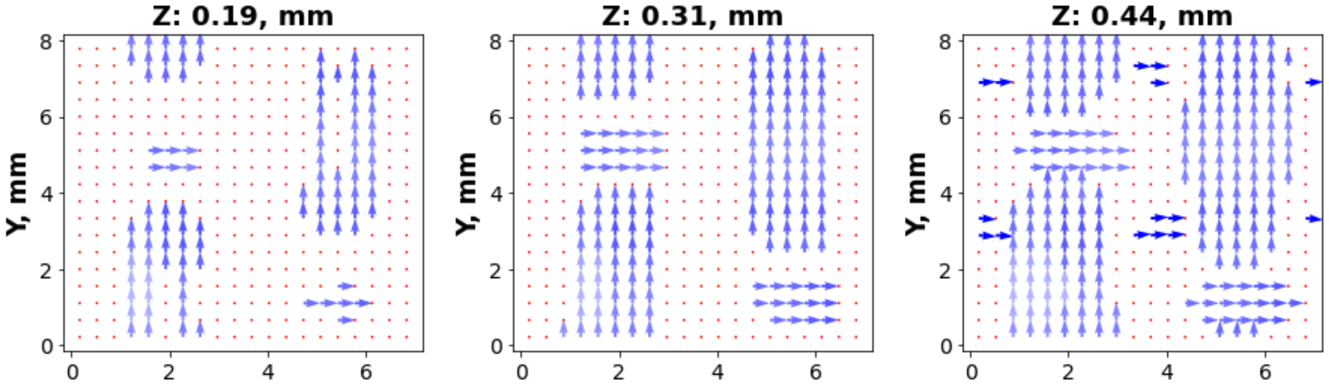


Dense model

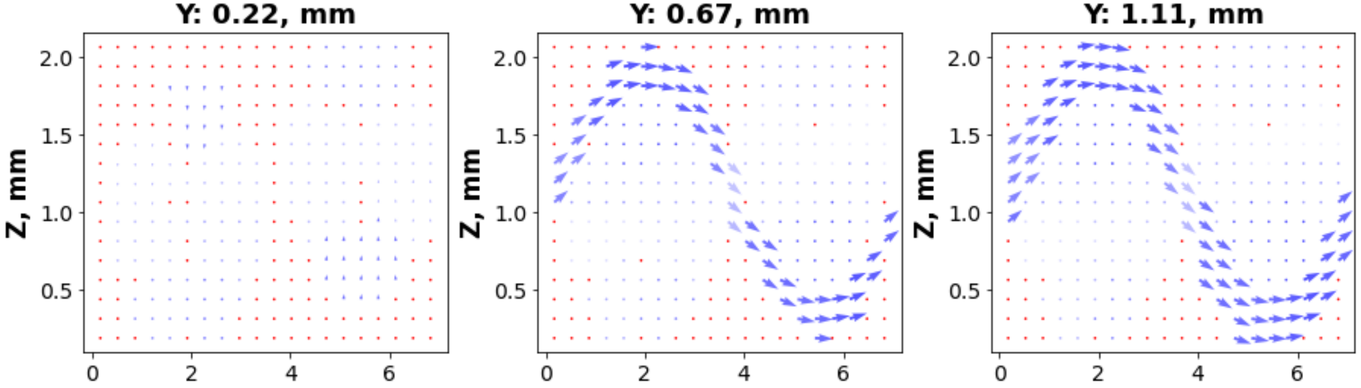


2D slices for visual representation

Horizontal XY plane



Vertical XZ plane



Challenges. Problem statement

Challenges:

- Computational time for complex architectures can reach hours and days
- Design and optimisation of textiles requires to solve many different woven architectures

Problem statement

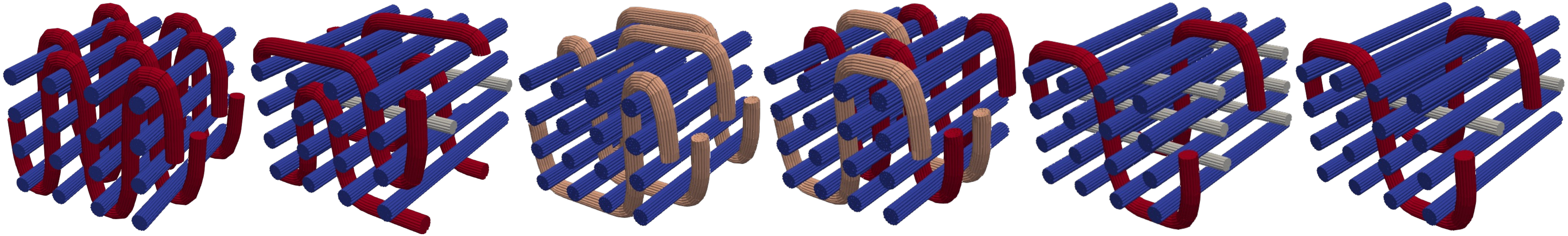
Capture the features of the fabric's deformation process by learning yarns behaviour from a variety of training exercises.

Generating training set. Case studies

Several weaving architectures with different yarn paths were considered.

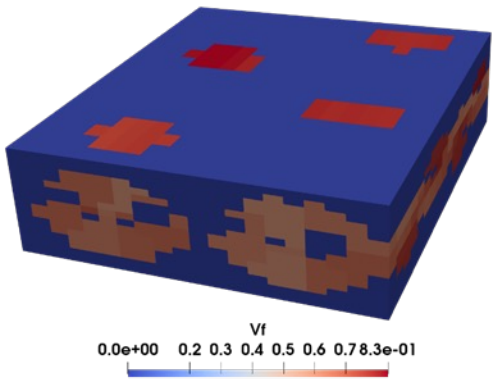
- Unit cell size is fixed
- Same number of timesteps within each case study (to keep the timestep constant)
- Areal weight of the fabric recalculated
- Periodicity condition

Total 4000 weaving architectures with different yarn paths were generated for further neural network training.
Each case study is solved throughout 15 timesteps

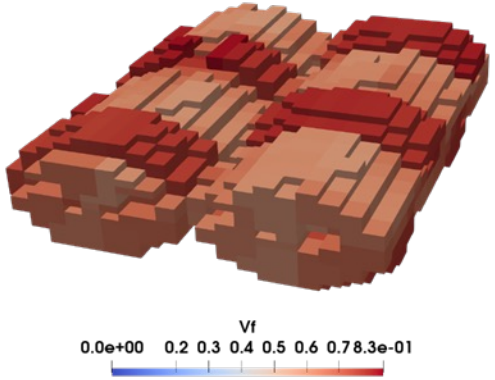


Training data

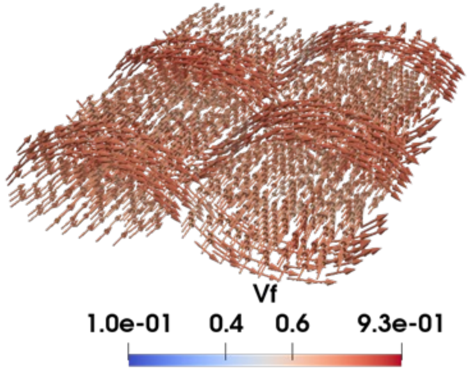
Voxel Model



Voxel Model (no matrix)



Voxel Model (glyph view)

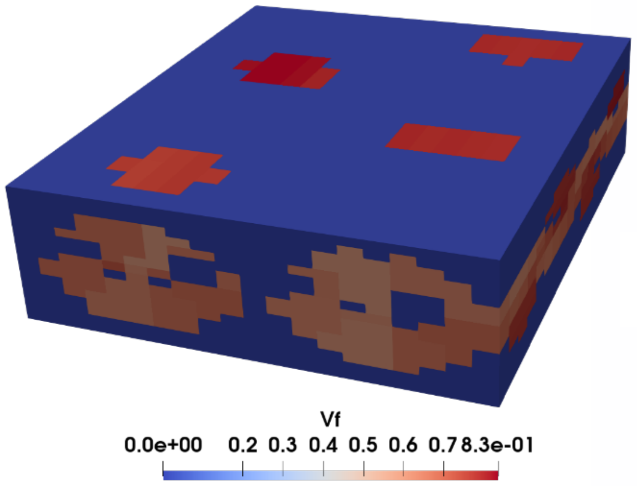


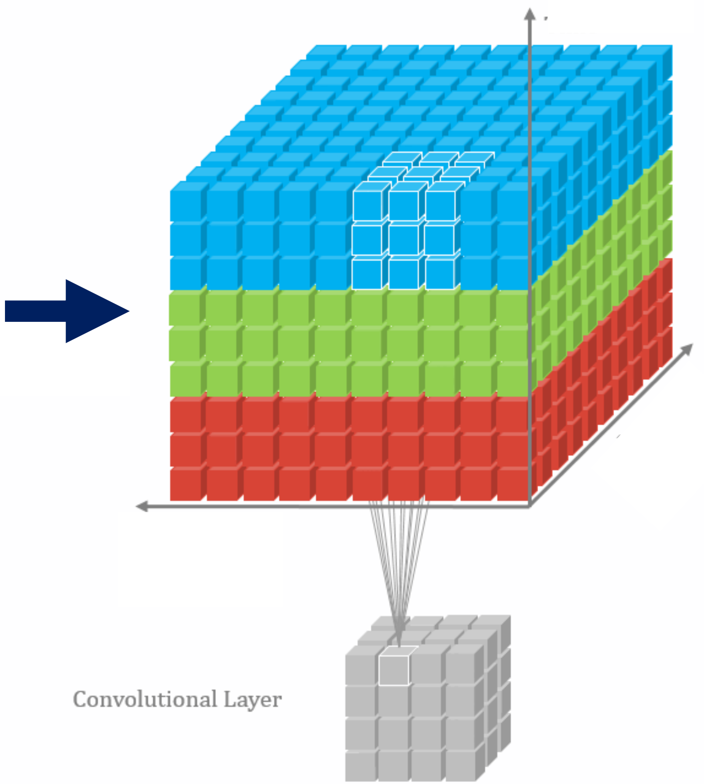
The outcomes of all case studies are joined in one database for further postprocessing

	X	Y	Z	Section	Vf	Orient_X	Orient_Y	Orient_Z	Voxel_type	Step number	Case study	Time
4536	0.29167	0.66667	0.29149	374	0.79940	0.97410	0.00643	0.22602	Fibre	21	1	5.00000
4537	0.87500	0.66667	0.29149	26	0.80966	0.00472	0.99998	-0.00519	Fibre	21	1	5.00000
4538	1.45833	0.66667	0.29149	378	0.82741	0.98738	0.00988	-0.15809	Fibre	21	1	5.00000
4539	2.04167	0.66667	0.29149	380	0.76004	0.97423	-0.02011	-0.22464	Fibre	21	1	5.00000
4540	2.62500	0.66667	0.29149	701	0.70915	0.00047	0.99357	0.11321	Fibre	21	1	5.00000
...	...	...	...	...	...	...	...	...	...	...	...	...
4747	0.87500	7.33333	3.20641	271	0.69631	-0.00449	0.99353	-0.11347	Fibre	21	1	5.00000
4748	1.45833	7.33333	3.20641	271	0.69631	-0.00449	0.99353	-0.11347	Fibre	21	1	5.00000
4749	2.04167	7.33333	3.20641	947	0.70357	-0.00142	0.99655	0.08297	Fibre	21	1	5.00000
4750	2.62500	7.33333	3.20641	947	0.70357	-0.00142	0.99655	0.08297	Fibre	21	1	5.00000
4751	3.20833	7.33333	3.20641	947	0.70357	-0.00142	0.99655	0.08297	Fibre	21	1	5.00000

Learning features.
3D Convolutional Network Layer

- Similar to 3D image analysis
- Facilitates the extraction of relevant features from the deformed yarns geometry
- Analyses voxel point cloud at every time step
- Input features:
  - Fibre volume fraction
  - Fibre orientation

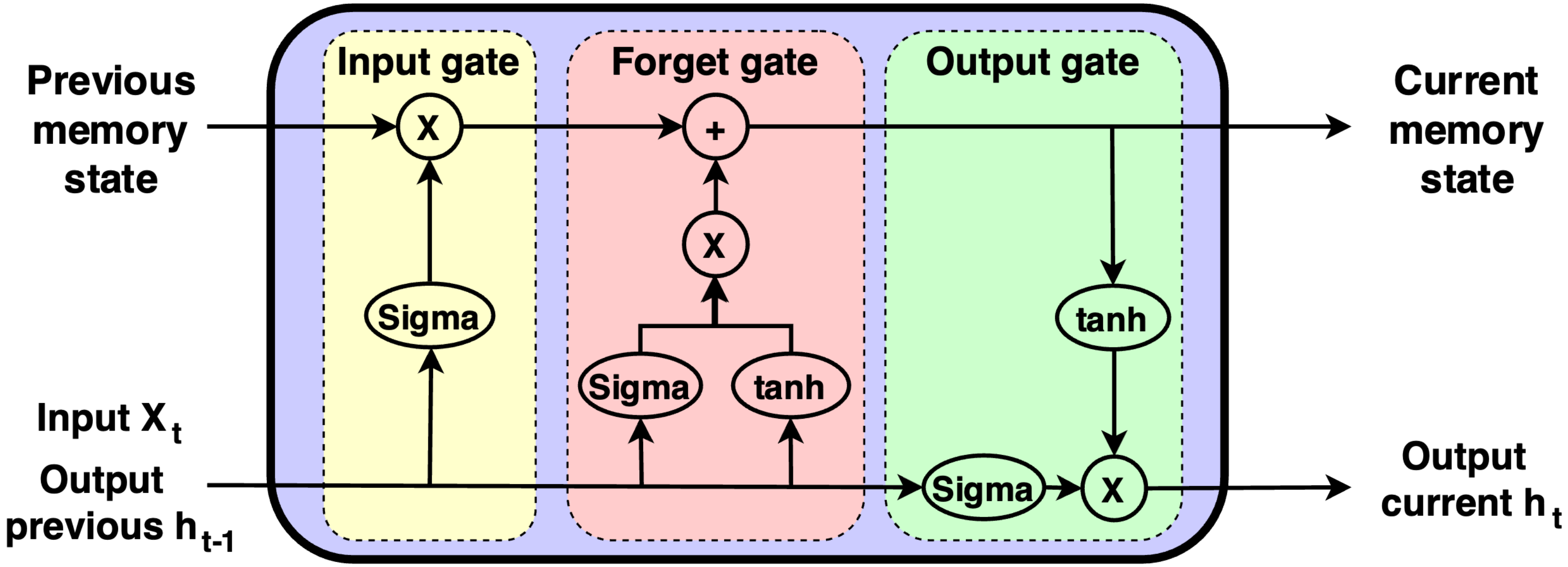




Learning deformation evolution

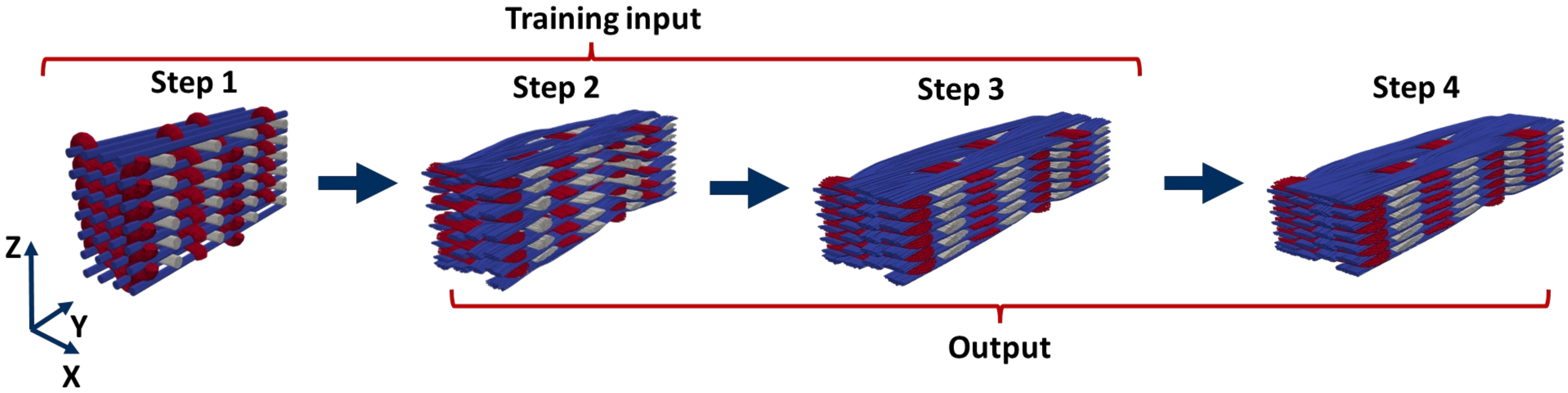
Recurrent Networks (**Long Short-Term Memory**)

- A powerful tool for modeling sequential data
- Passes relevant information down the chain to make predictions
- Network selectively remembers or forgets information from previous time steps



Input/Output for the training

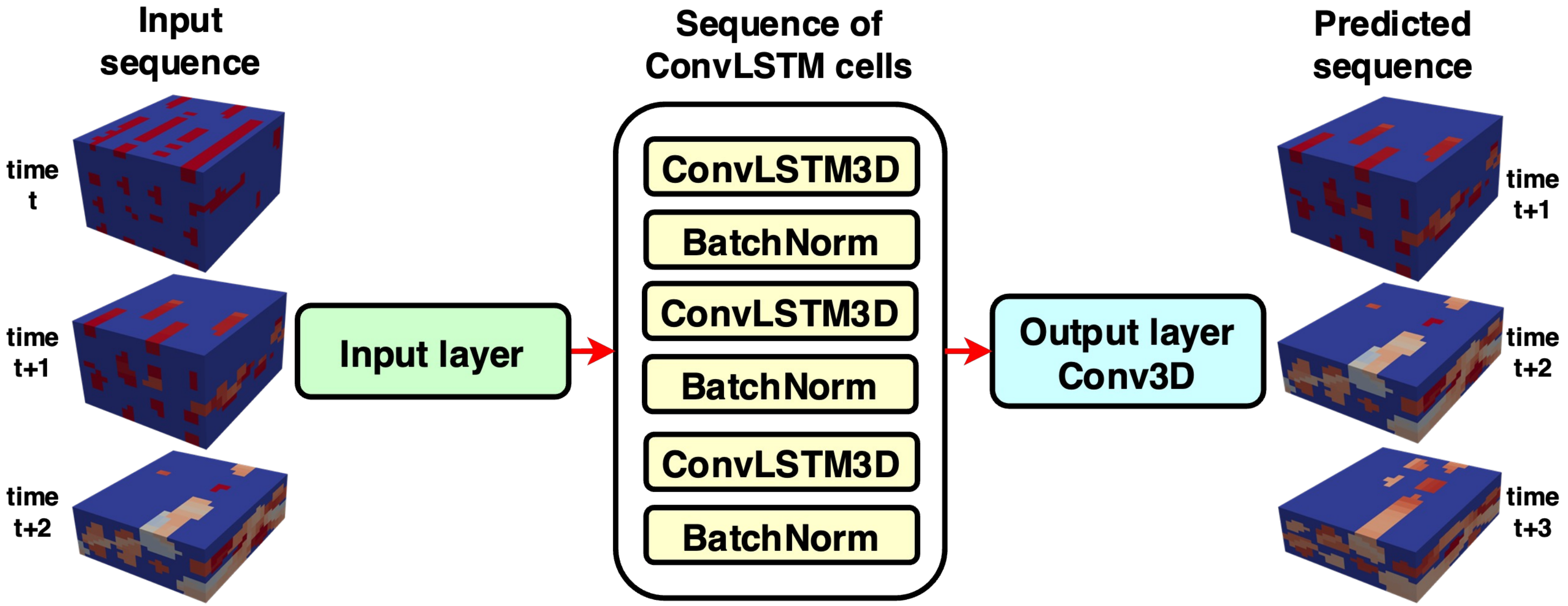
- Resulting set of solution timeframes is split into input and output sequences.
- Output sequence is defined by shifting forward input sequence by one timeframe



ConvLSTM3D approach

Input/output: 6-dimensional tensor

[case_study,
timeframe,
x_dim,
y_dim,
z_dim,
[fibre_vol, angle_1, angle_2]]



Advantages :

- Simplicity
- No intermediate steps
- Reliability

Disadvantages:

- High demand for computational resources

Encoder-Decoder approach

Step 1: Train encoder-decoder network

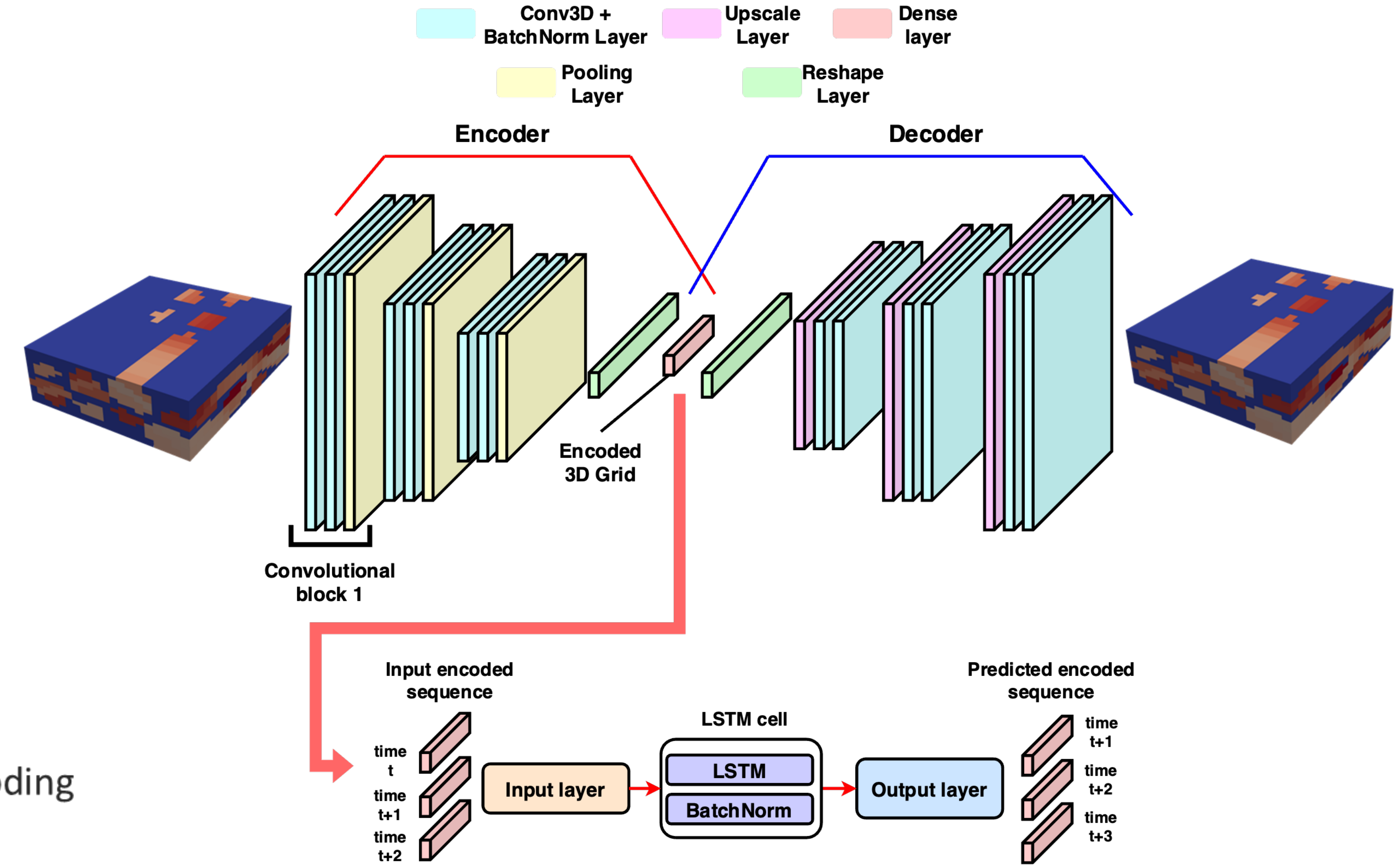
Step 2: encode training data

[case_study,
timeframe,
x_dim,
y_dim,
z_dim,
[fibre_vol, angle_1, angle_2]]

→

[case_study,
timeframe,
encoded_data]

Step 3: train new network



Advantages :

- Flexibility
- Lower computational requirements

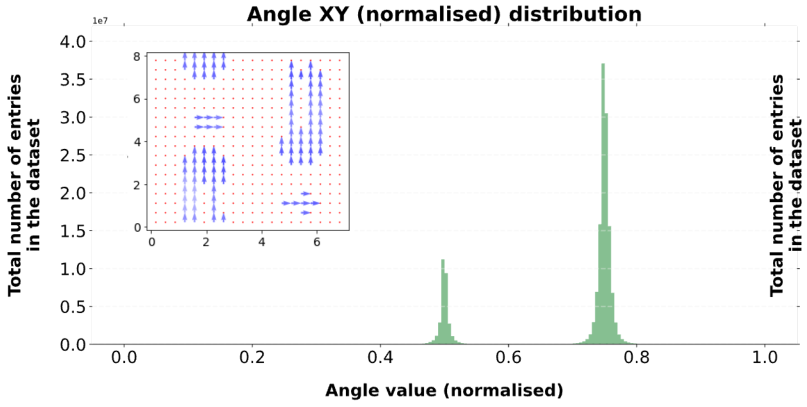
Disadvantages:

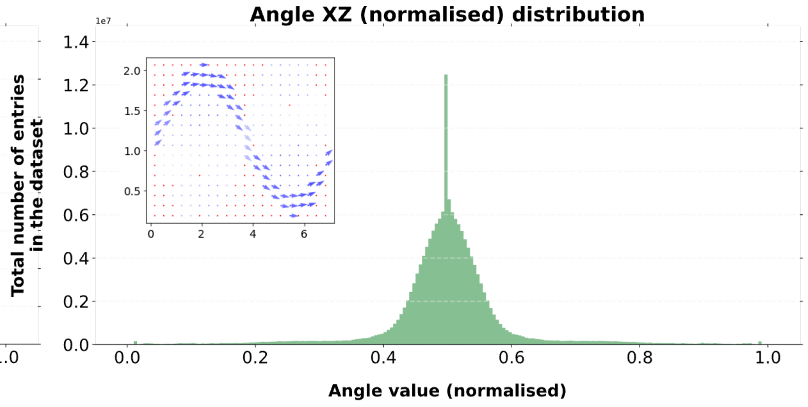
- Additional error during encoding-decoding
- Complexity of architecture

Data preprocessing

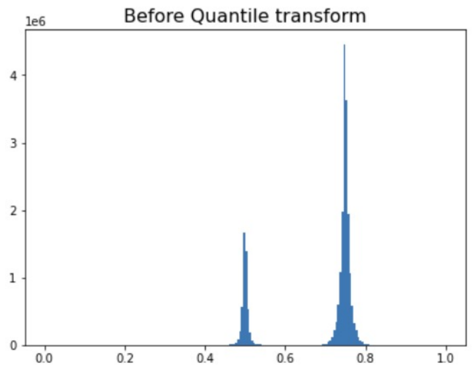
Data preparation

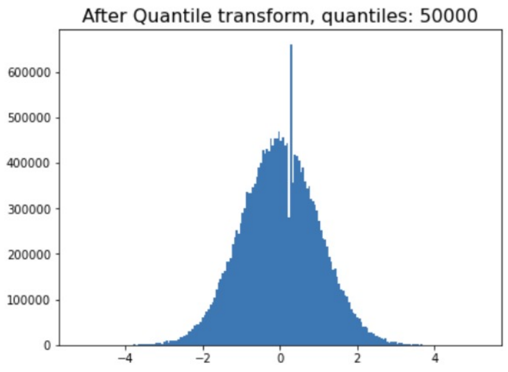
- Checking for outliers, bad case studies
- Normalisation, the network output is [0, 1]
- Data reshaping into 6D tensors

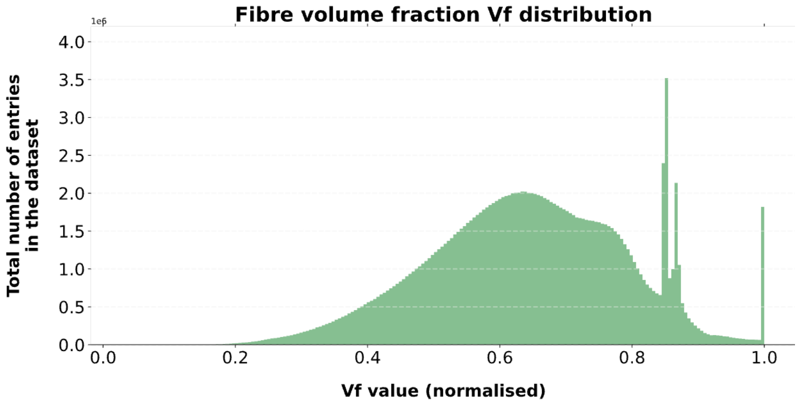




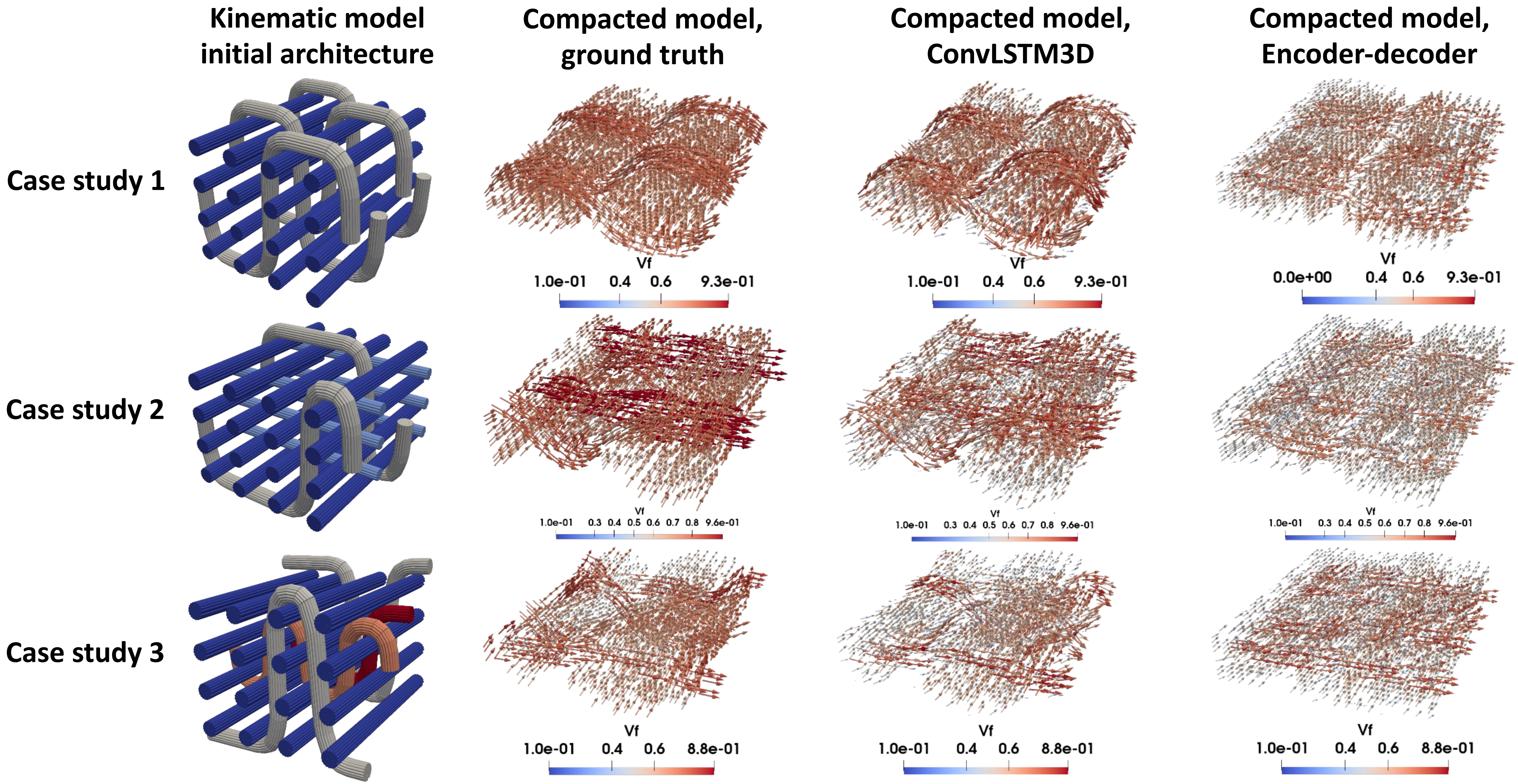
Ideal representation







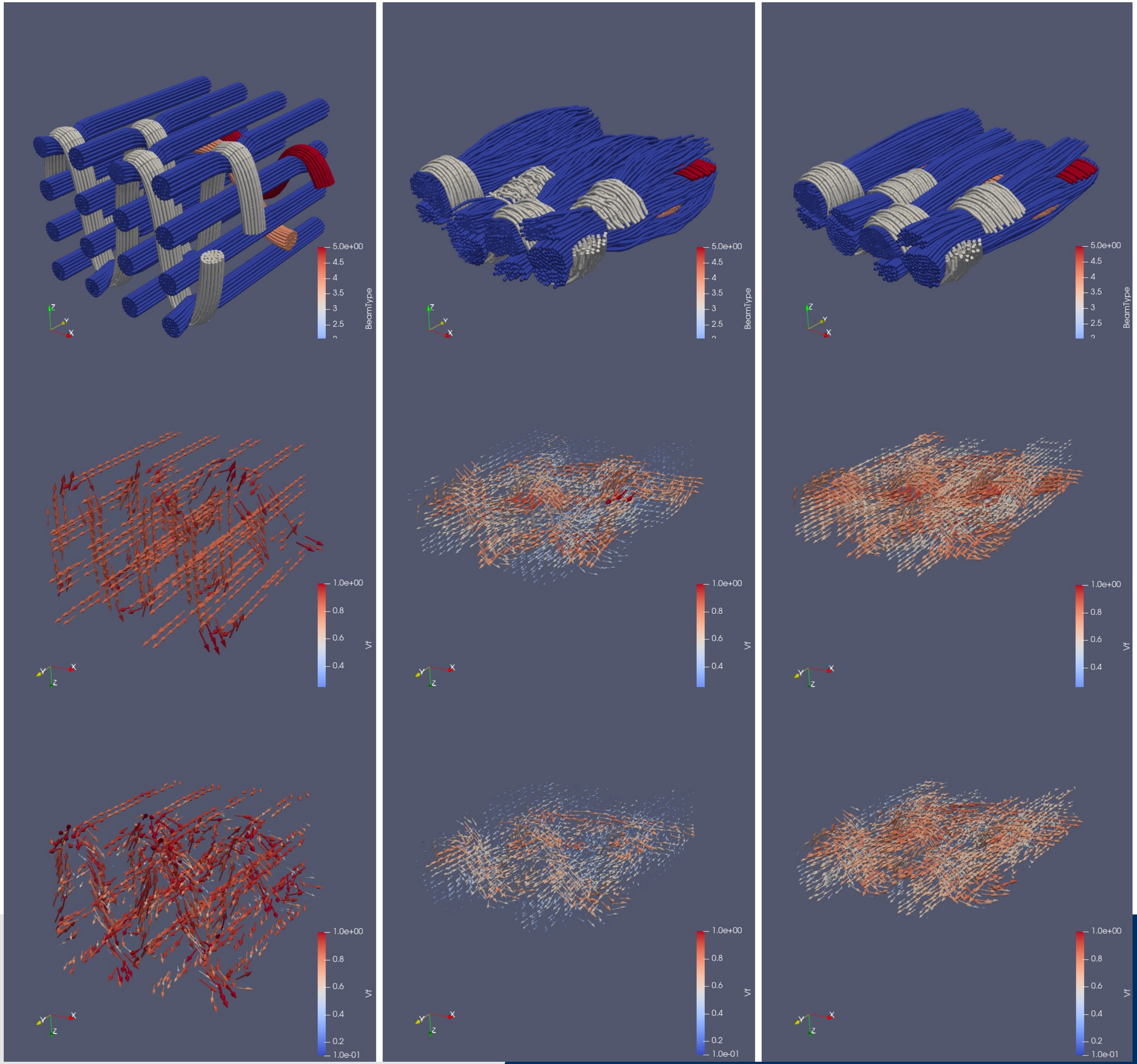
Prediction. 3D representation



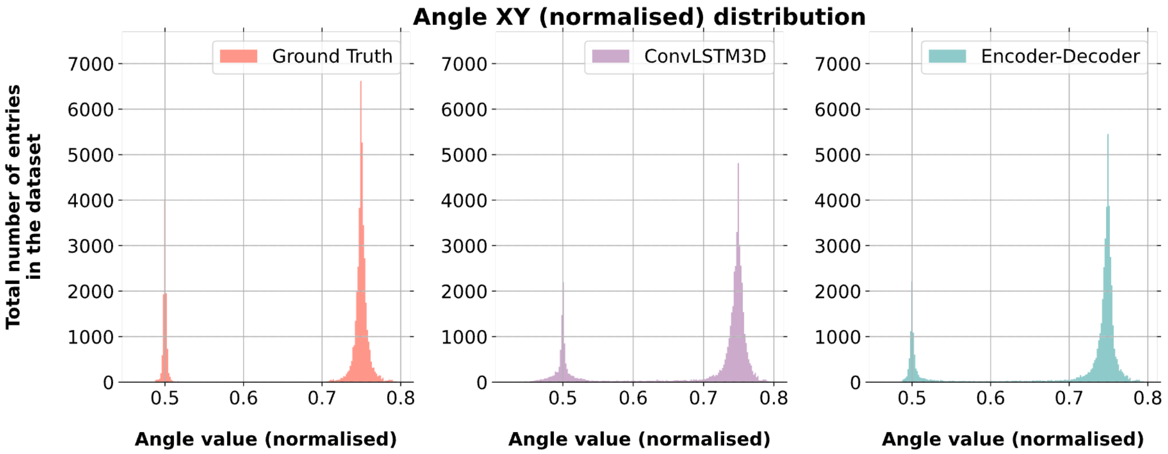
Kinematic model

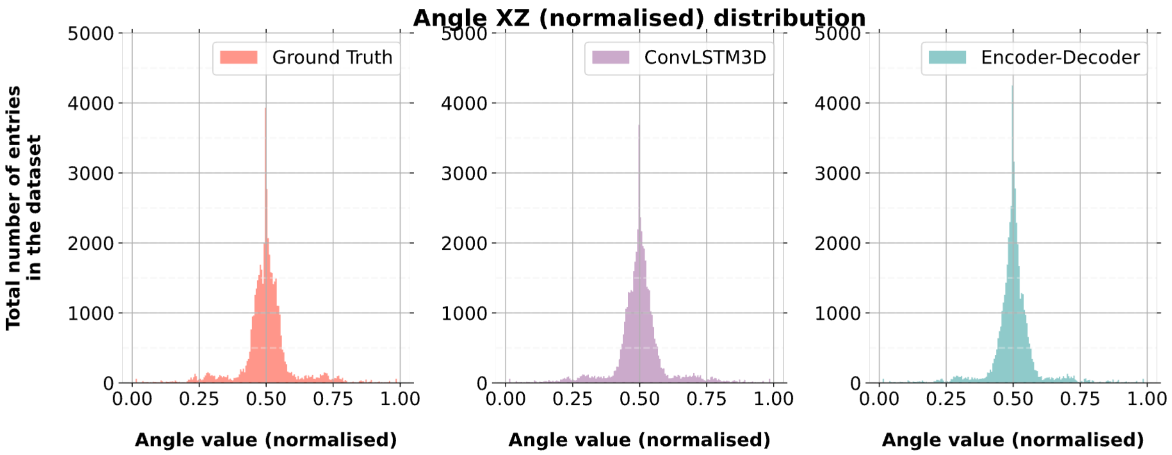
Ground truth

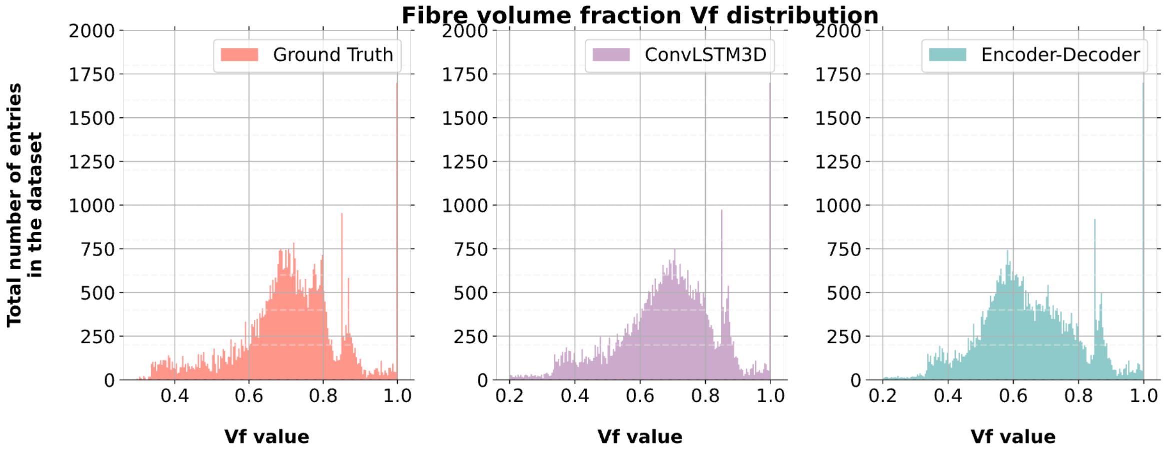
Prediction



Results. Features distribution







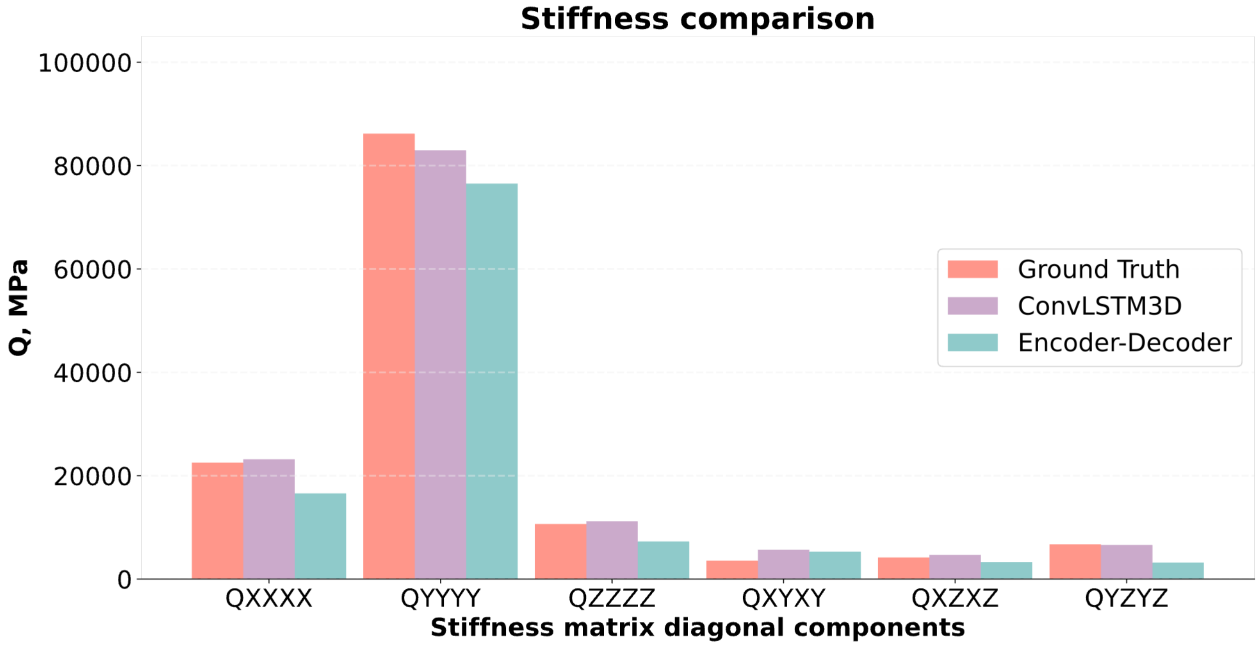
Results. Average properties

Averaging properties for the voxelised volume

Stiffness tensor

$$Q^X = \begin{bmatrix} Q_{XXXX} & Q_{XXYY} & Q_{XXZZ} & Q_{XXXY} & 0 & 0 \\ & Q_{YYYY} & Q_{YYZZ} & Q_{YYXY} & 0 & 0 \\ & & Q_{ZZZZ} & Q_{ZZXY} & 0 & 0 \\ & & & Q_{XYXY} & 0 & 0 \\ & & & & Q_{XZXZ} & Q_{XZYZ} \\ Sym & & & & & Q_{YZYZ} \end{bmatrix}$$

Comparison ground truth/prediction



Conclusions

- Deep learning approach to predicting 3D woven geometry is confirmed
- Computational time required for prediction is insignificant
- Different network architectures are suitable for the considered problem
- Encoder-decoder approach requires more tuning to output a reliable prediction

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