Towards neural network-based numerical friction models

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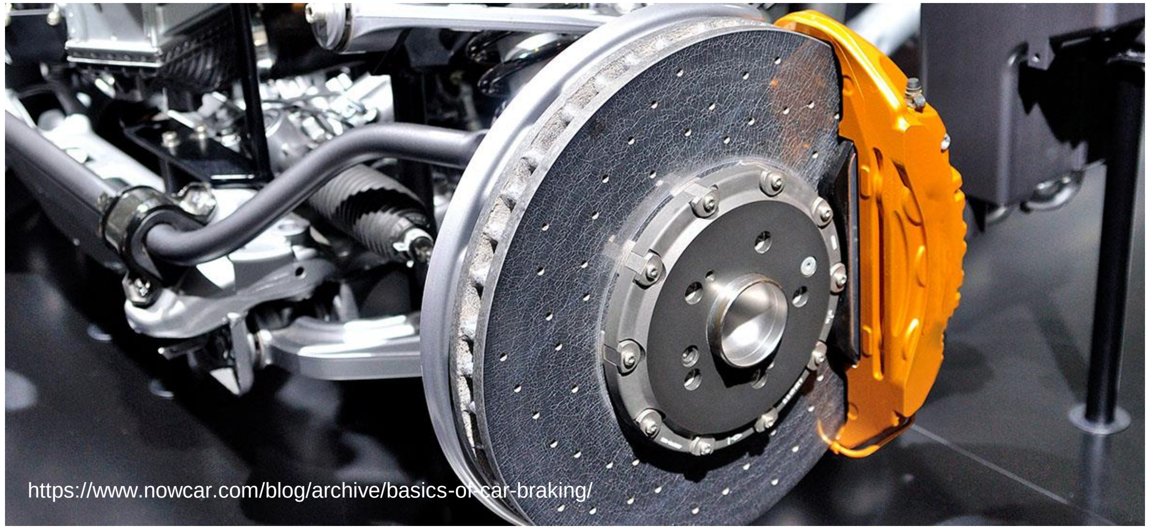
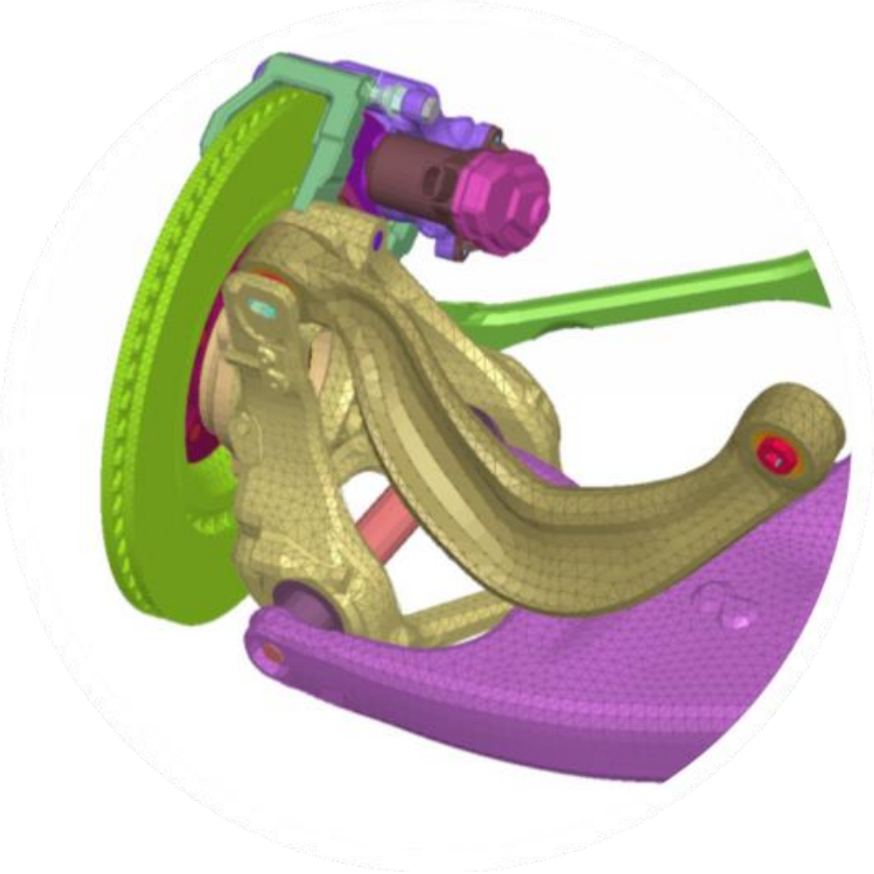
DOI: https://doi.org/10.15480/882.4561

Motivation

- Frictional contact behavior is hard to describe
- Large variety of parameters (velocity, pressure, temperature, humidity, load history,…)
- Difficult to represent contact behavior in numerical simulations properly
- Analytical models often highly simplified
- Data-driven approaches open up new opportunities





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Proceeding

I. Setup of a transient 2-D plane-stress Finite Element model
II. Training and validation data generation
III. Selection of a neural network for regression
IV. Network training and performance assessment
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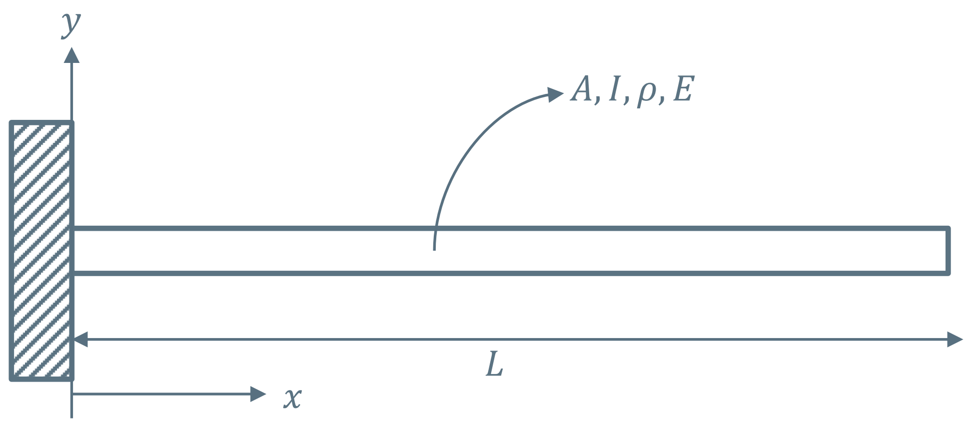
Cantilever beam model

- Slender cantilever beam obeying Euler-Bernoulli beam theory



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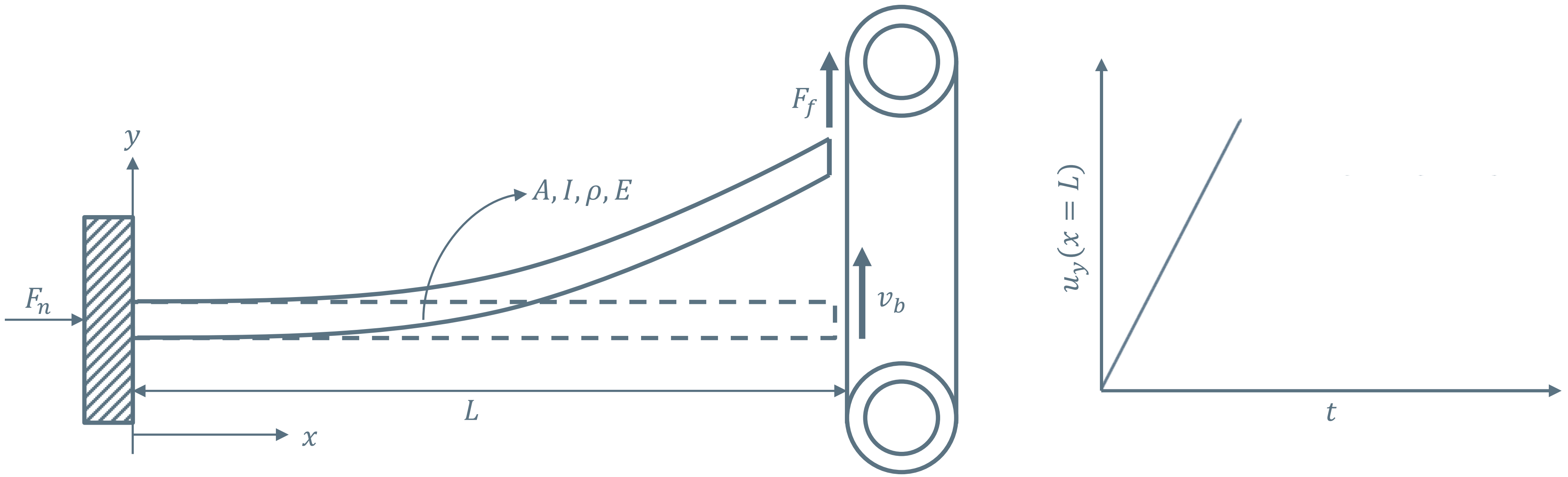

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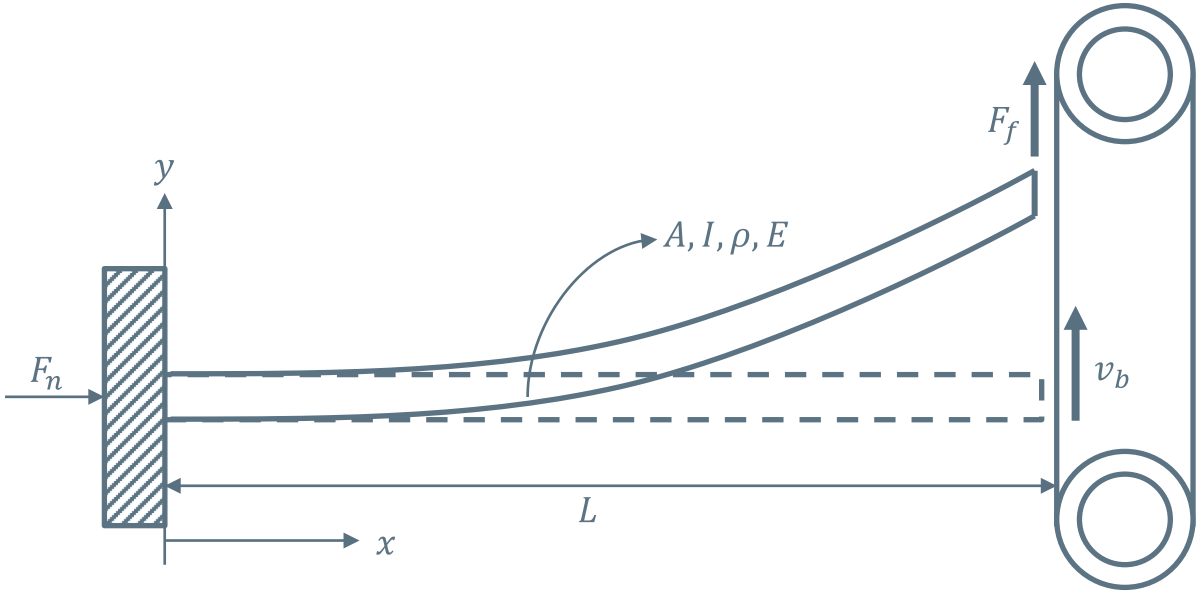
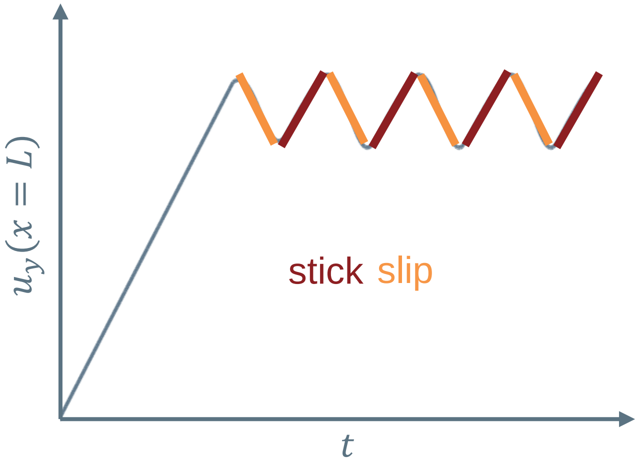
- Frictional contact with moving belt induces stick-slip vibration at the free end





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Cantilever beam model

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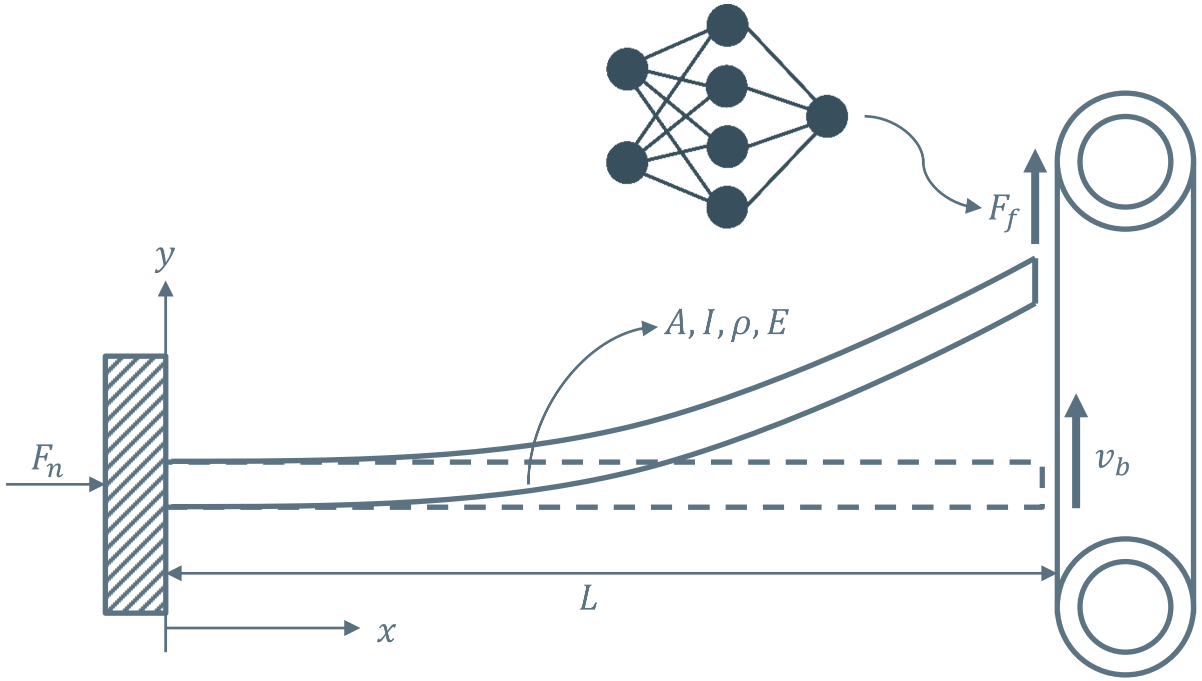
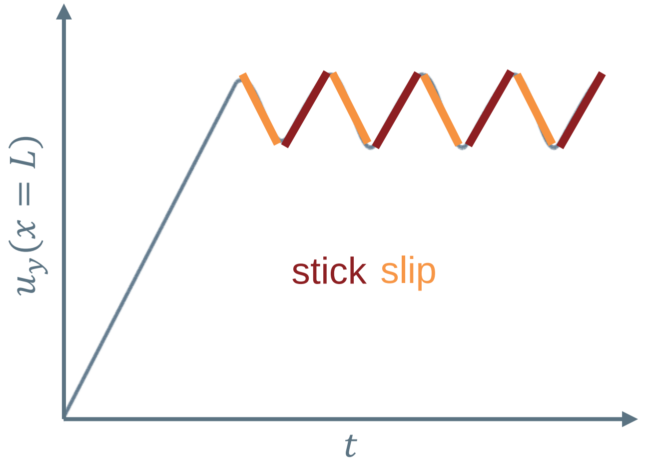
- Frictional contact with moving belt induces stick-slip vibration at the free end
- Kinetic friction force estimated by neural network model





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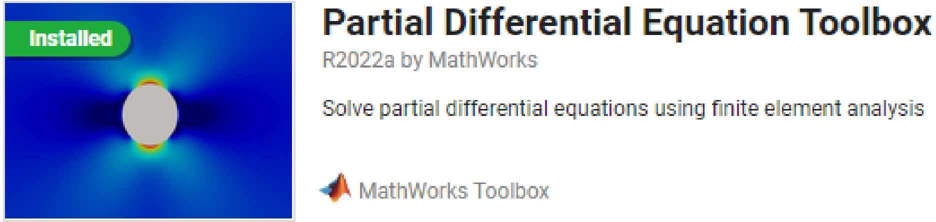

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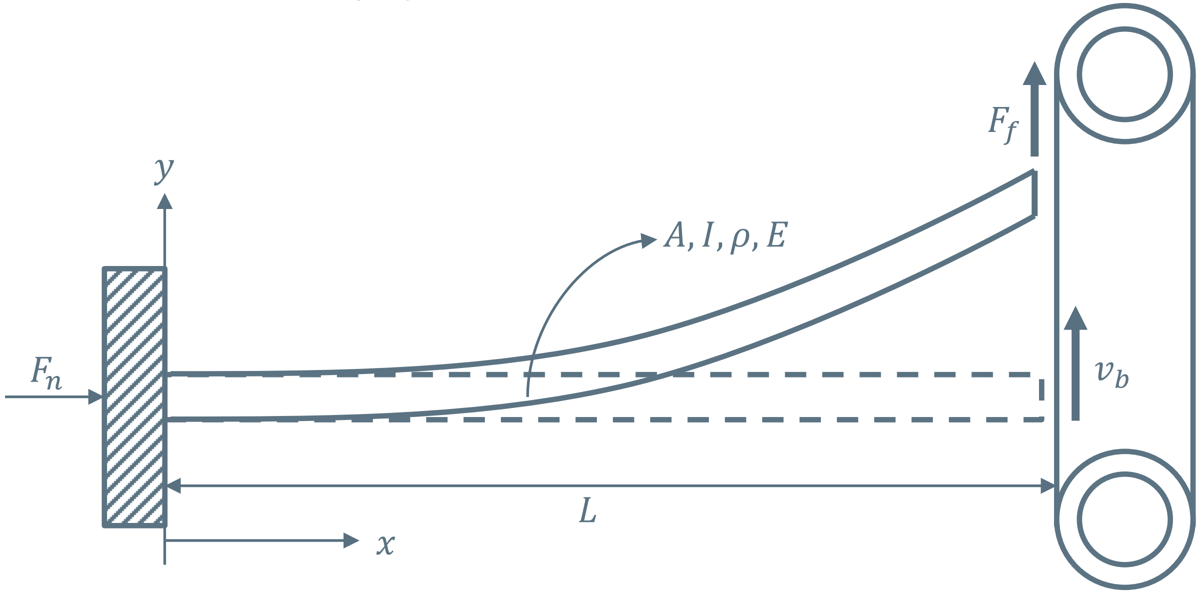

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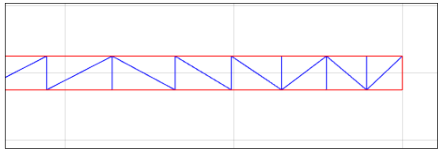
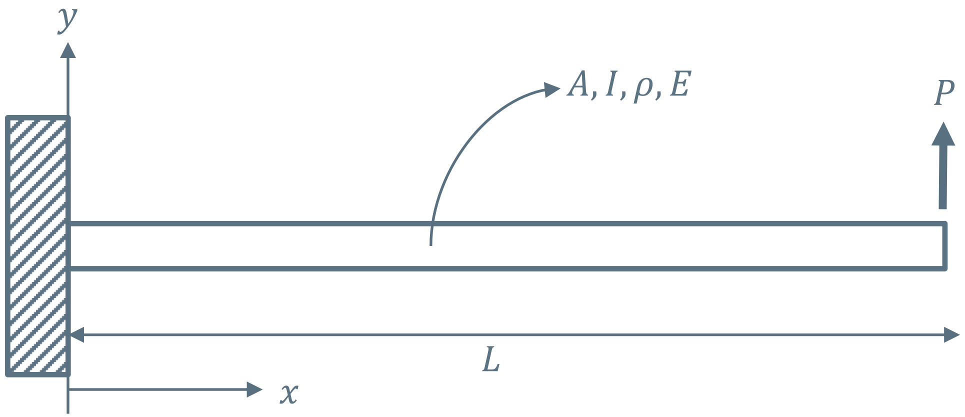
Mesh convergence study

- Static Finite Element analysis of a 2-D plane-stress problem
- Triangular mesh of quadratic Finite Elements
- Cantilever beam subjected to a point load at the free end





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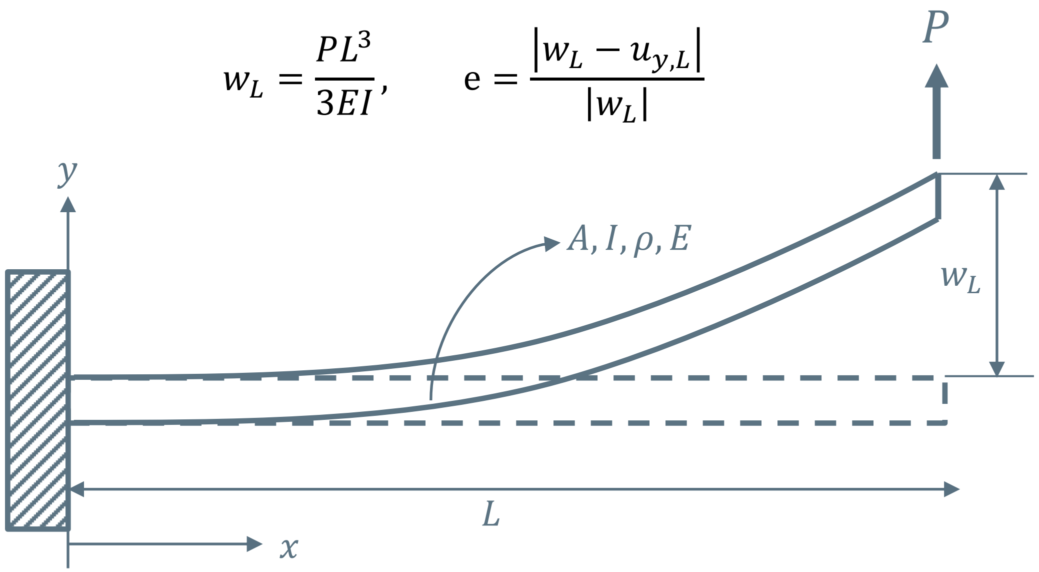
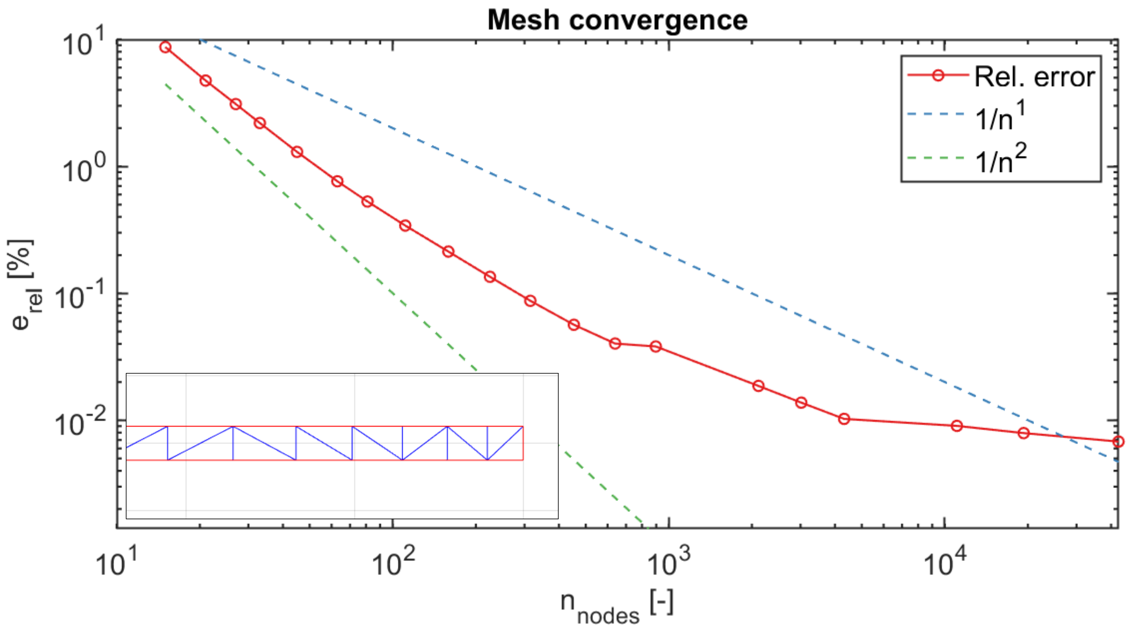
$$w_L = \frac{PL^3}{3EI}, \qquad e = \frac{|w_L - u_{y,L}|}{|w_L|}$$





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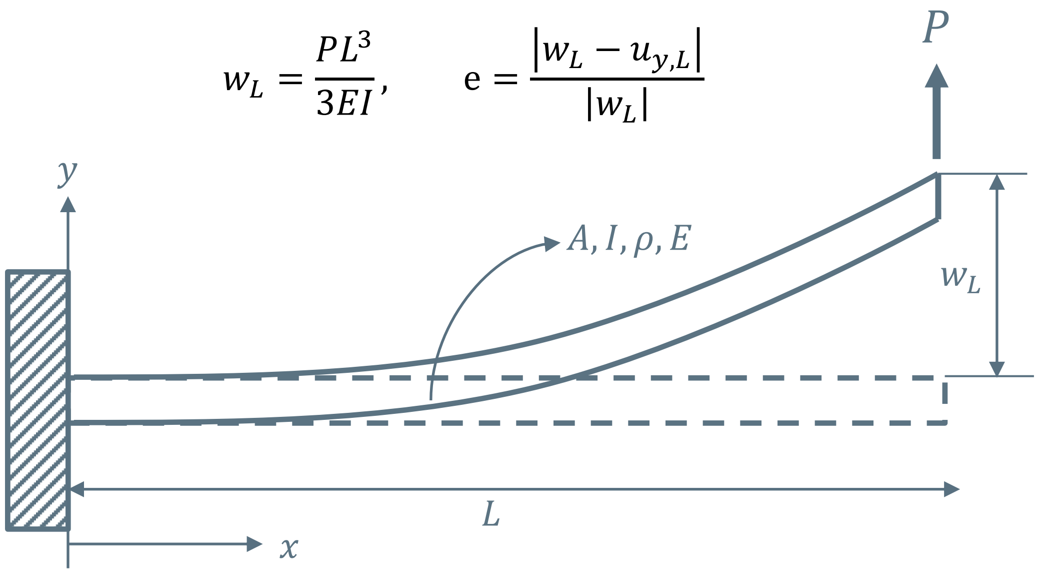

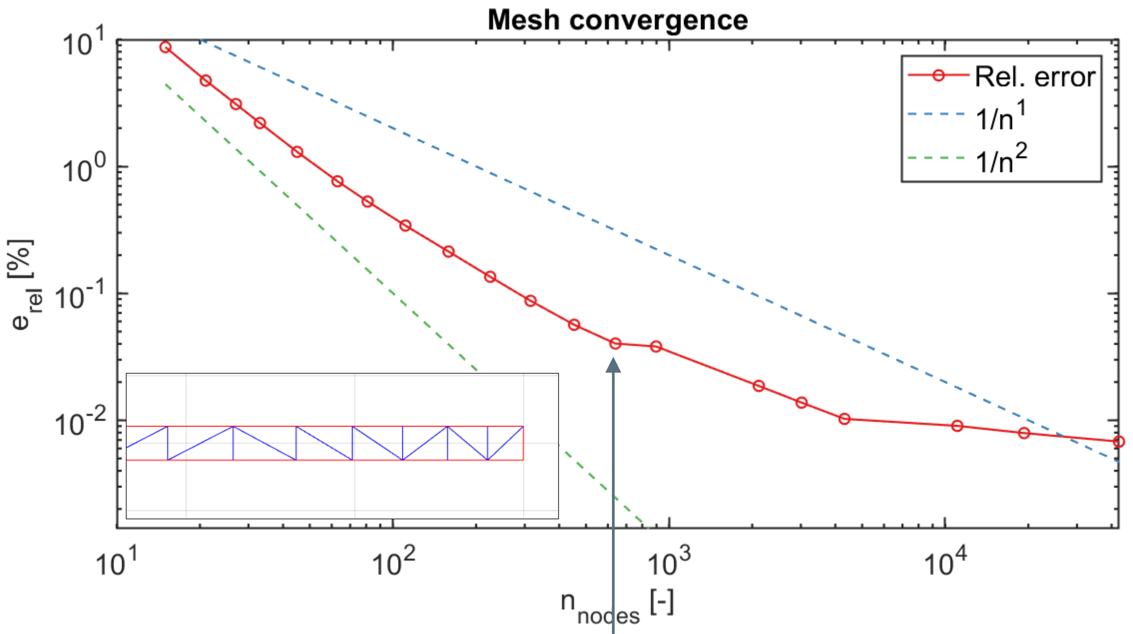

→ Choose $h_{max} = 0.02$

- Very low relative error
- Number of nodes still manageable

h = 0.1153,	nodes = 111,	e = 0.3417 %.
h = 0.0807,	nodes = 159,	e = 0.2133 %.
h = 0.0565,	nodes = 225,	e = 0.1350 %.
h = 0.0395,	nodes = 315,	e = 0.0873 %.
h = 0.0277,	nodes = 453,	e = 0.0565 %.
h = 0.0194,	nodes = 639,	e = 0.0402 %.
h = 0.0136,	nodes = 897,	e = 0.0381 %.
h = 0.0095,	nodes = 2113,	e = 0.0186 %.
h = 0.0066,	nodes = 3019,	e = 0.0138 %.

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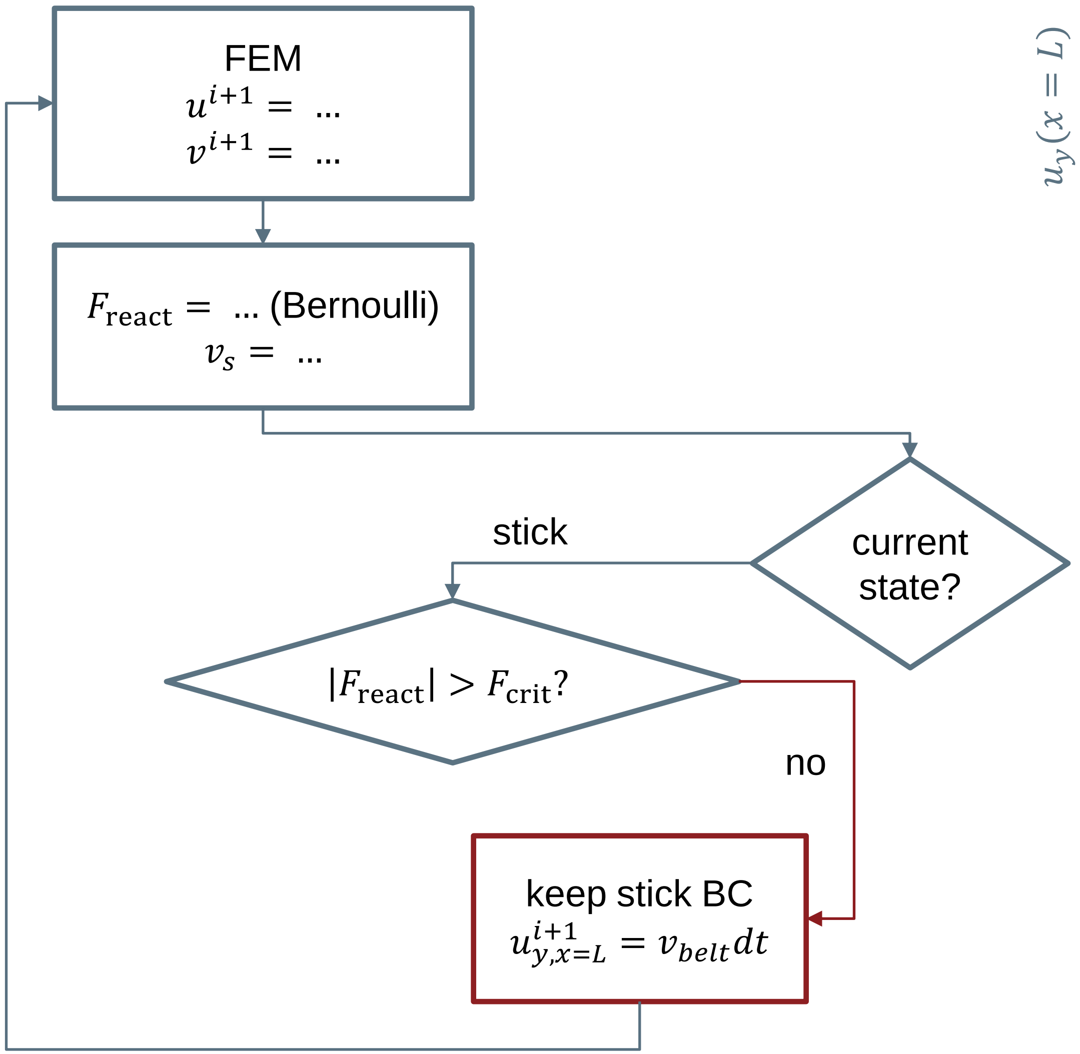
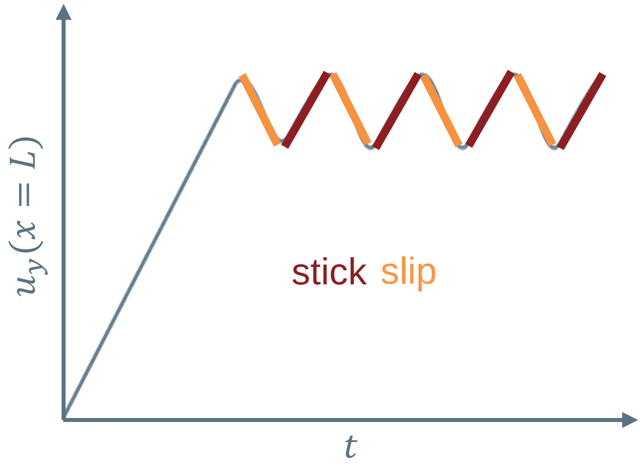
Transient Finite Element algorithm





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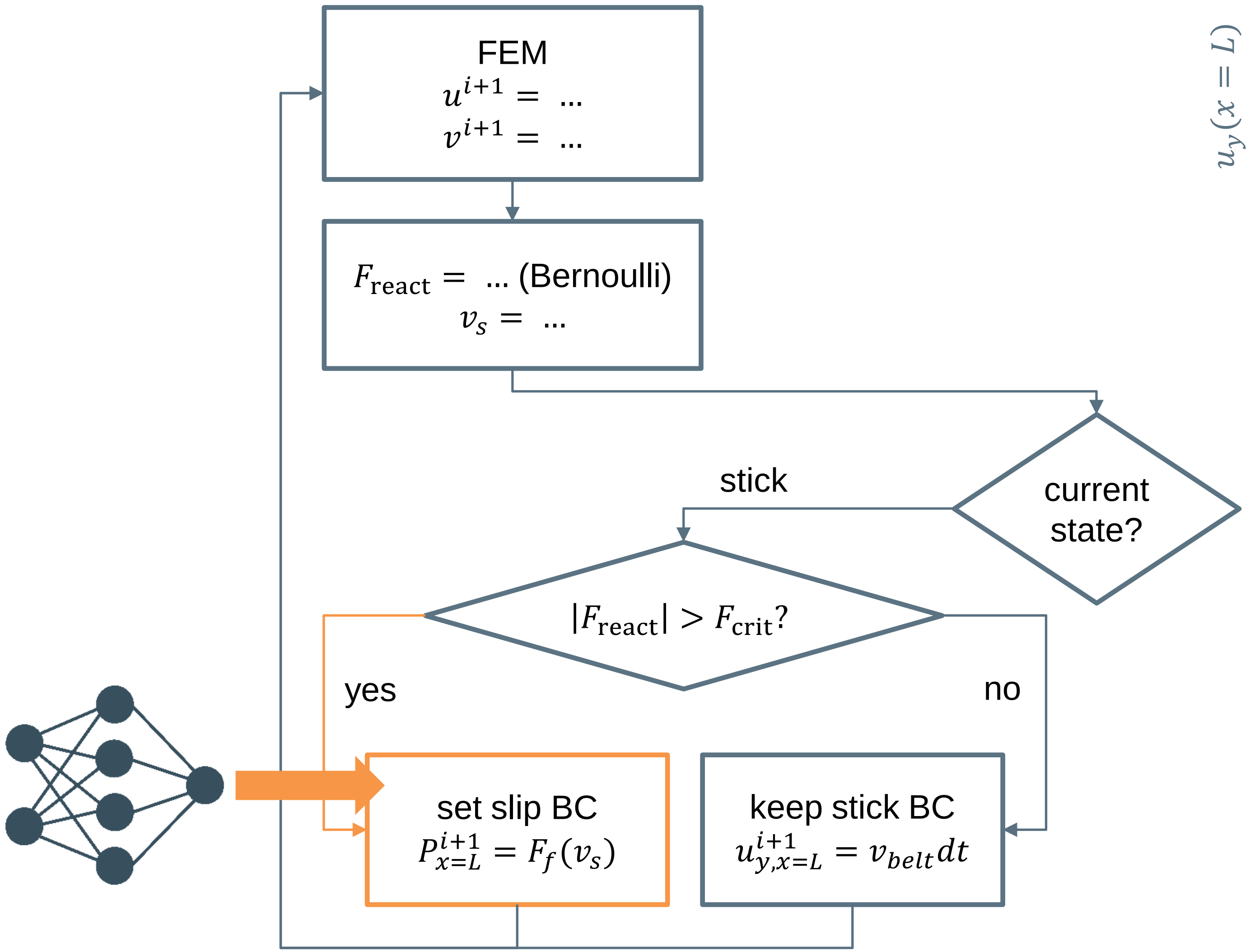

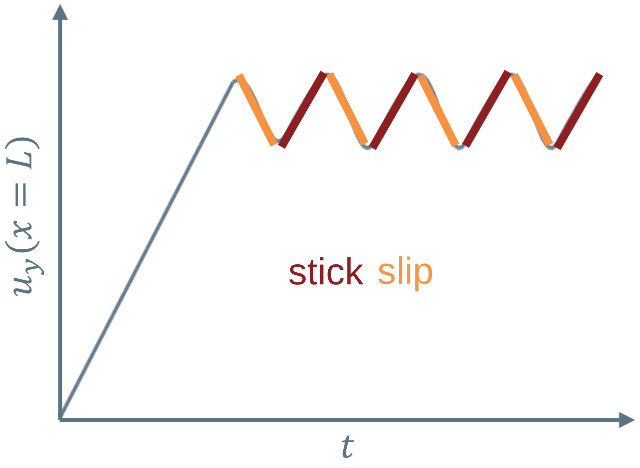

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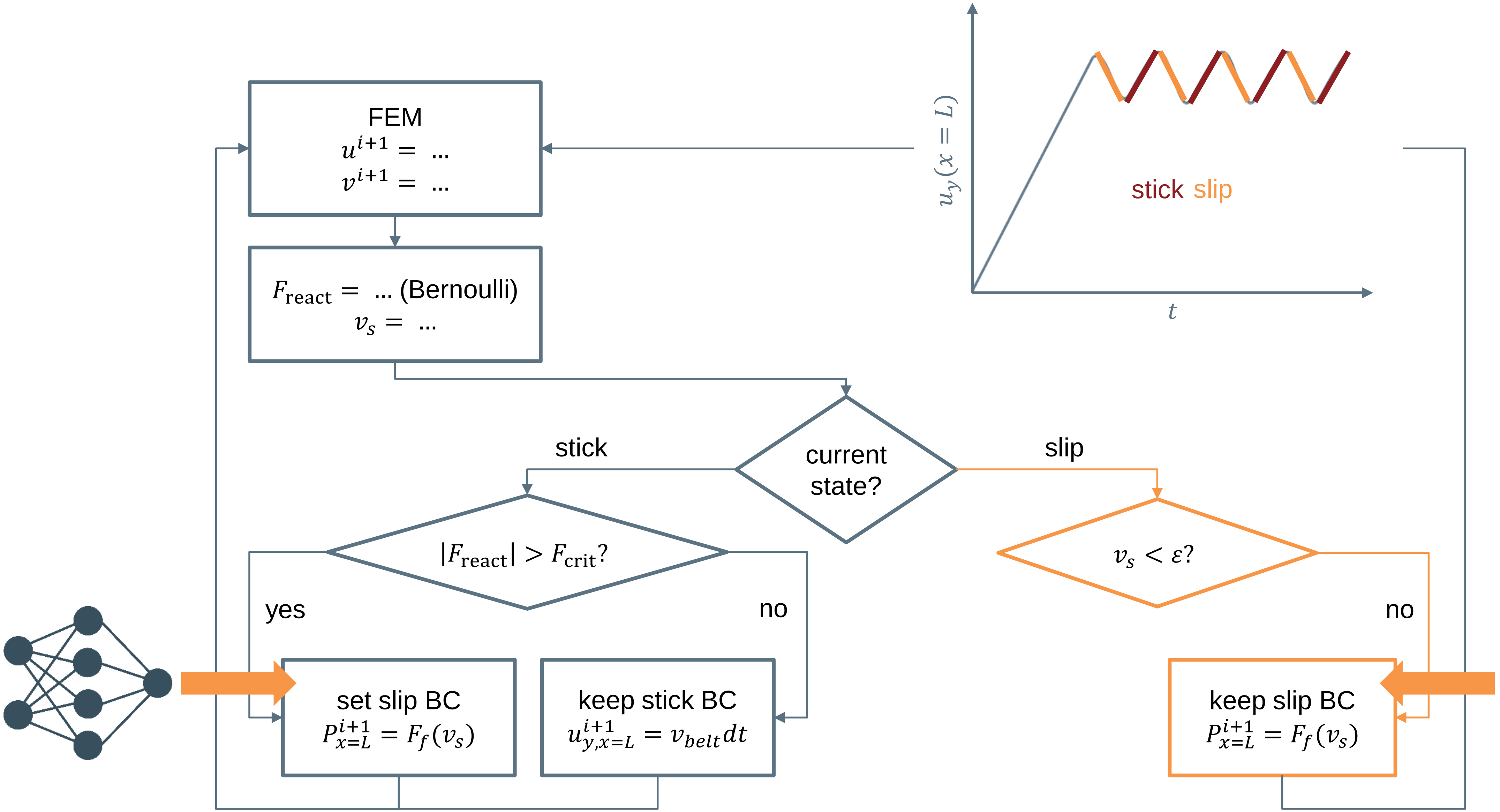

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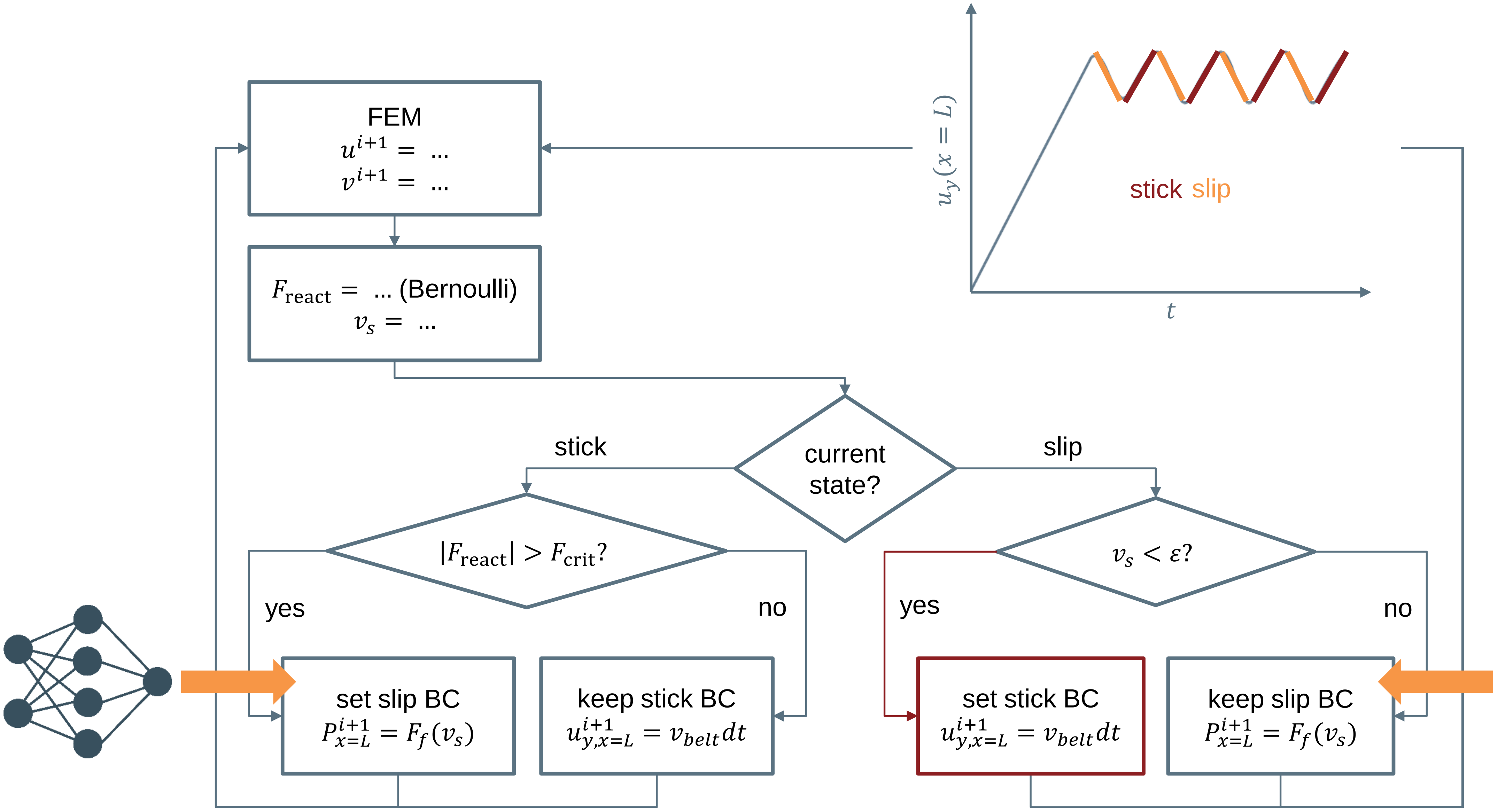

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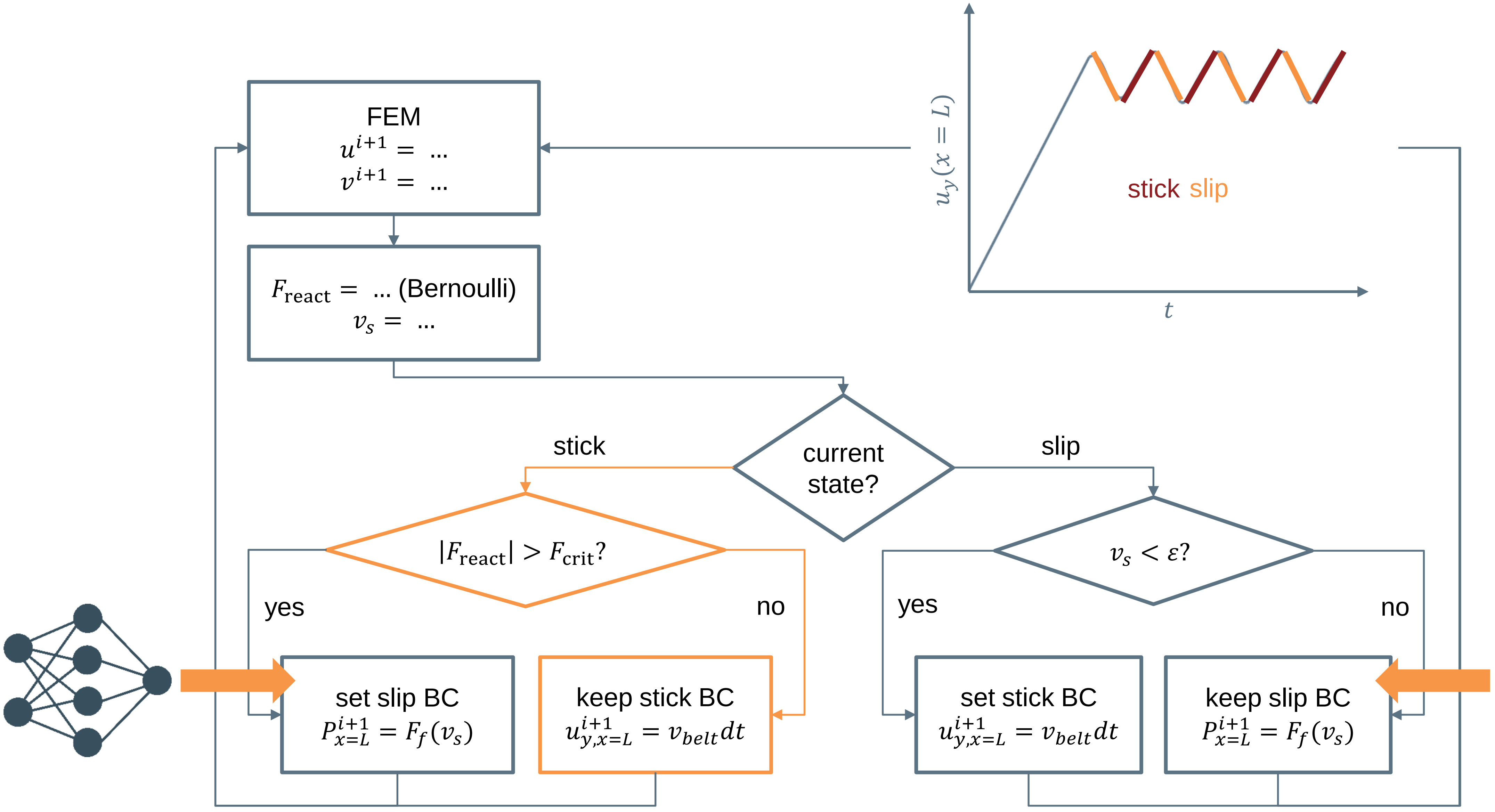

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DYNAMICS GROUP

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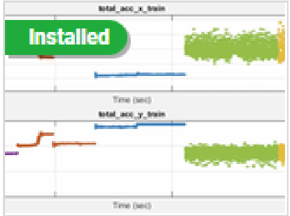


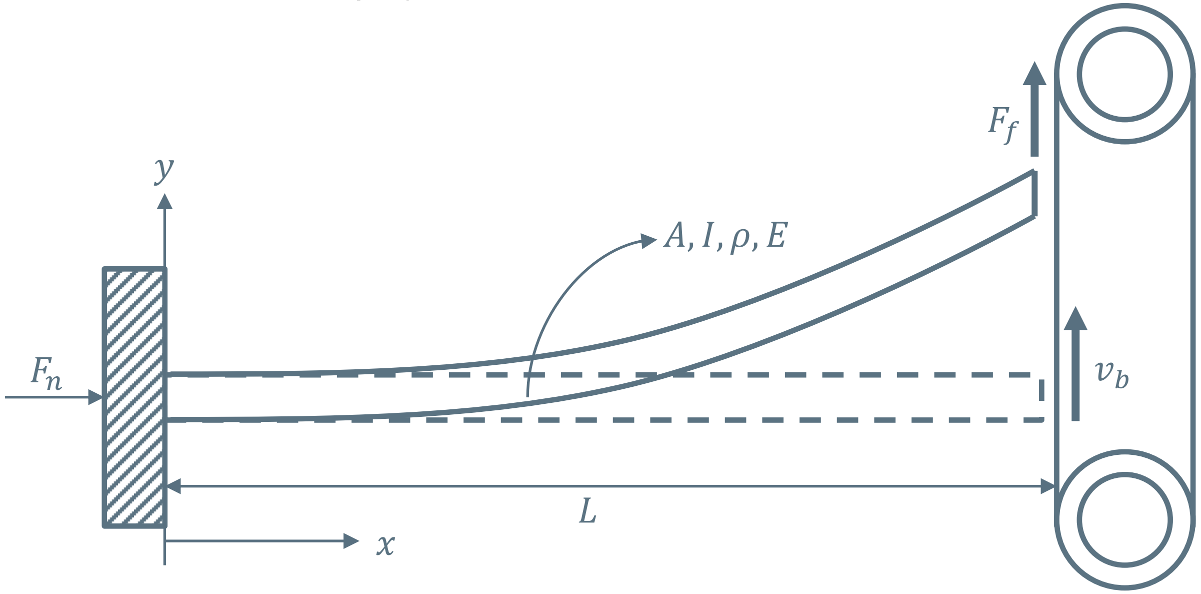
Statistics and Machine Learning Toolbox

R2022a by MathWorks

Analyze and model data using statistics and machine learning

MathWorks Toolbox

MATLAB®



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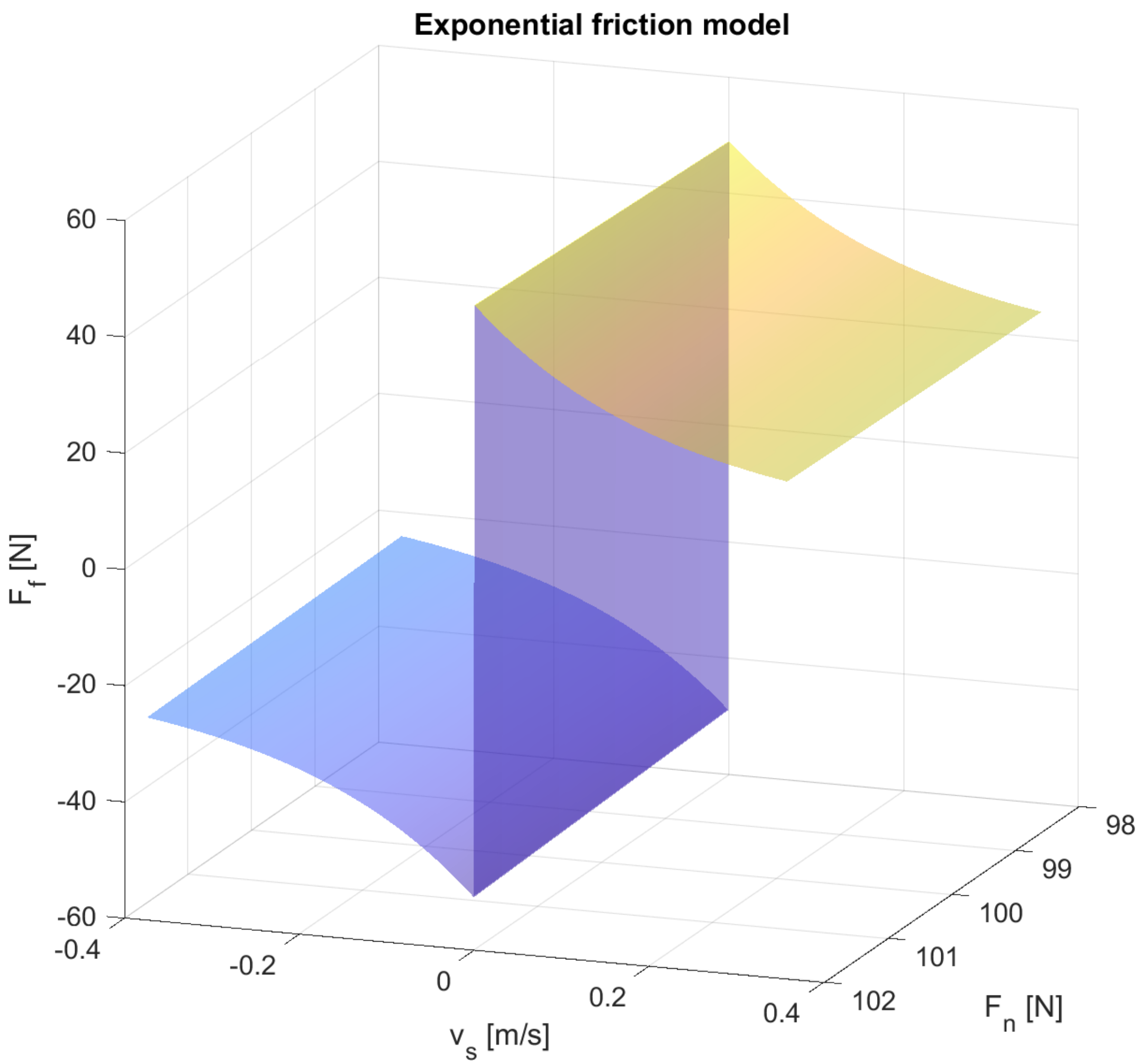
Friction data sampling and partitioning



Exponential-type friction model:

$$\mu(v_s) = \mu_k + (\mu_s - \mu_k)\mathrm{e}^{-\alpha|v_s|}$$

$$F_f(v_s) = \mathrm{sgn}(v_s) \times \mu(v_s) \times F_n$$

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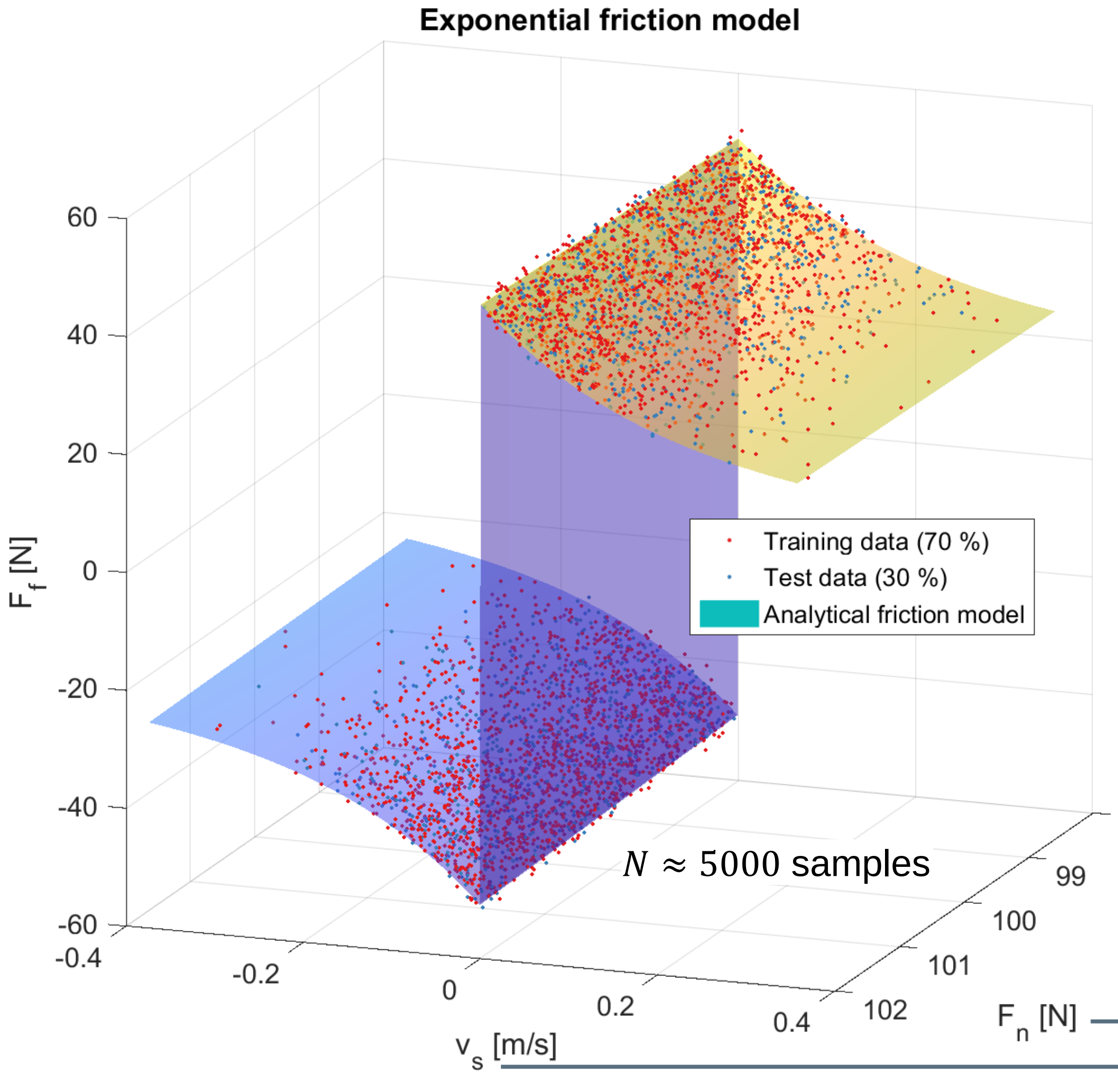

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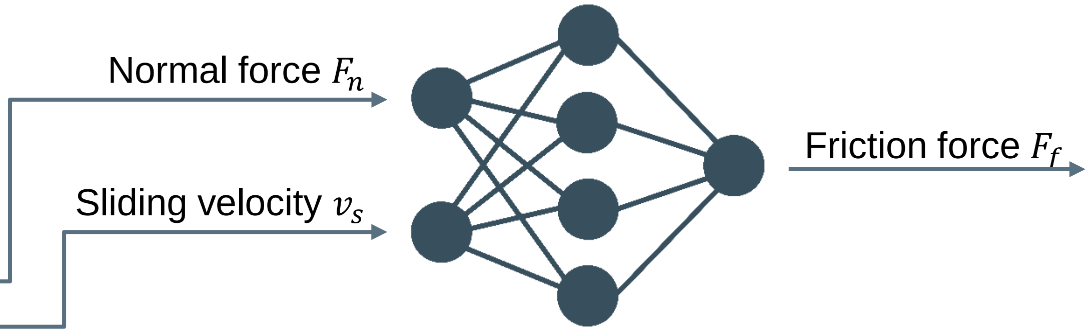
+ artificial noise

→ Mimic real measurement data



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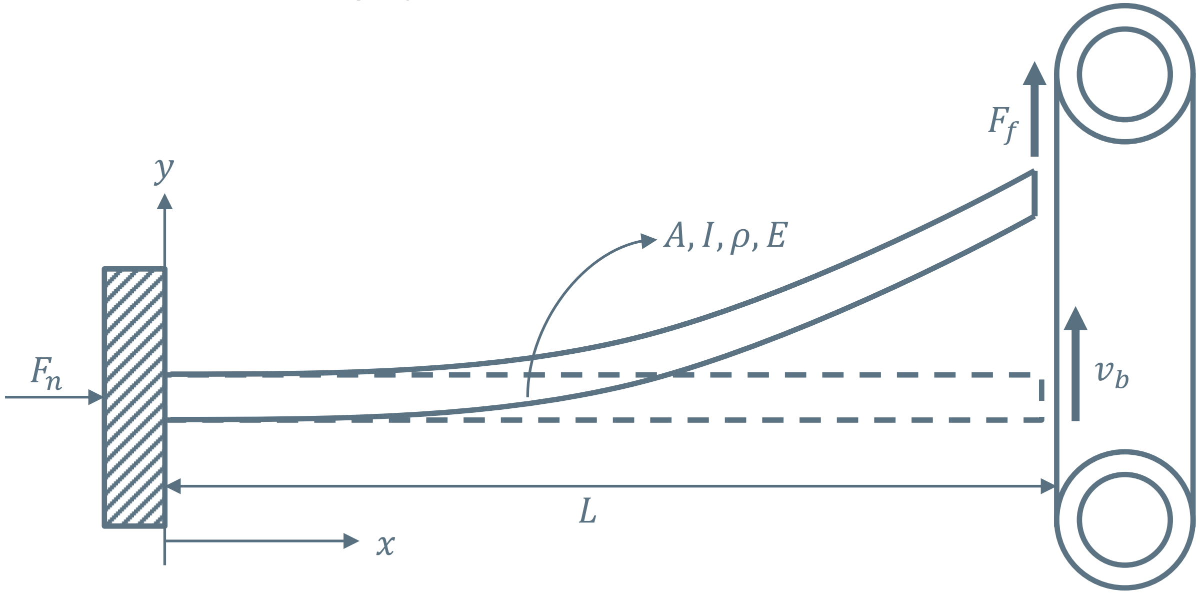

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Neural network selection

- Feedforward, fully connected neural network for regression
- Hyperparameter optimization studies

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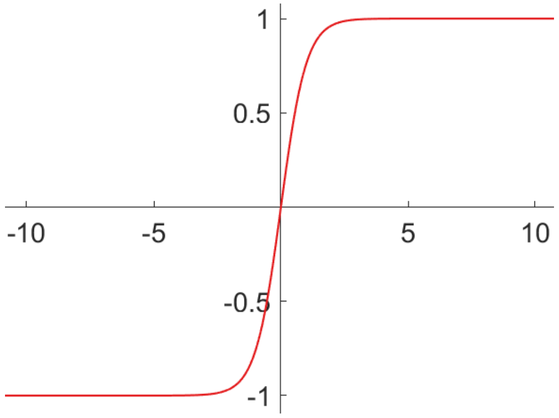
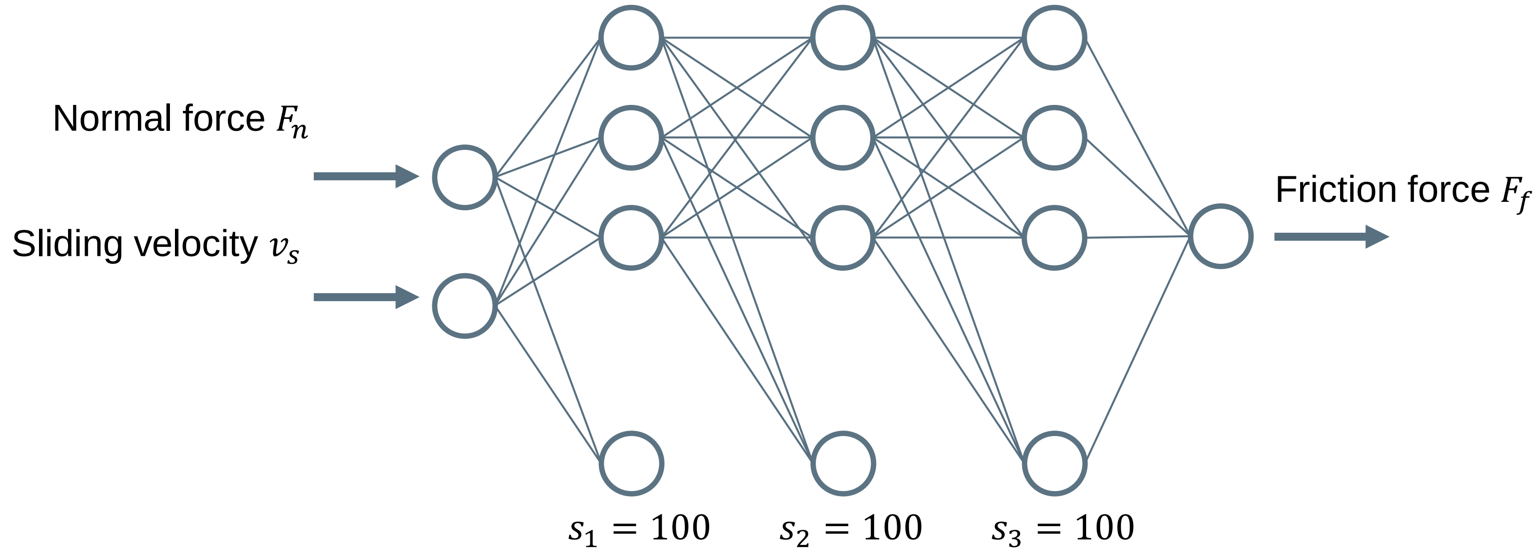
Hyperbolic tangent (tanh)





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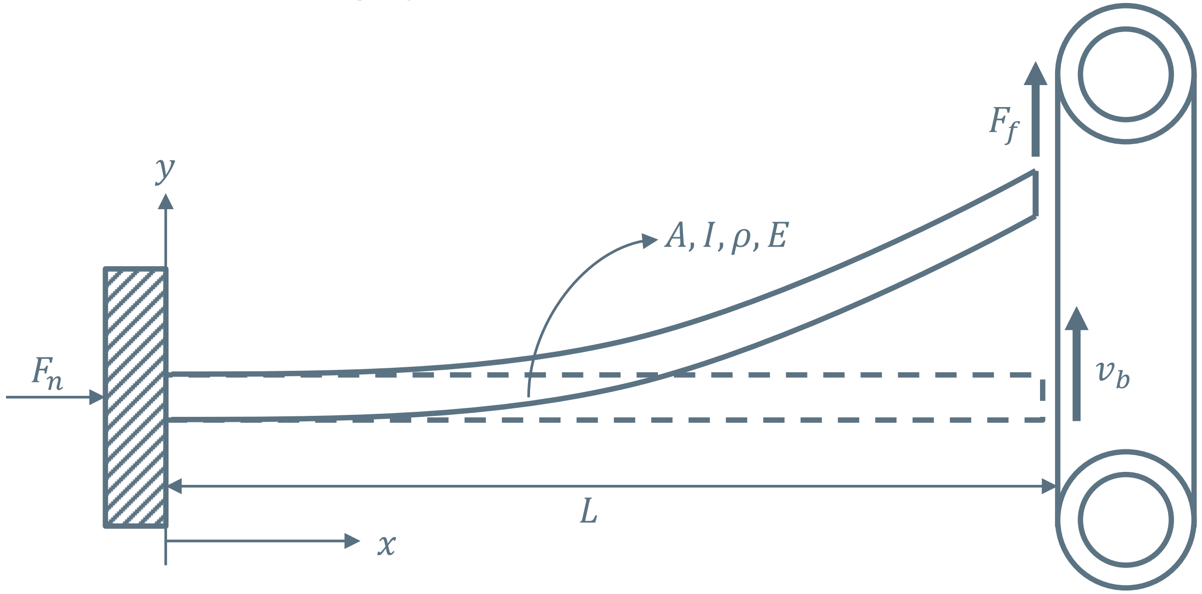

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Neural network training and performance

- Limited-memory BFGS optimization algorithm
- Minimizing MSE loss function

```
rnet = fitrnet(dataTrain, "Ff", ...
    "ValidationData", dataTest, ...
    "Activations",  "tanh", ...
    "Lambda",       0.004, ...
    "LayerSizes",   [100 100 100], ...
    "Standardize",  true, ...
    "StoreHistory", true, ...
    "Verbose",      true);
```

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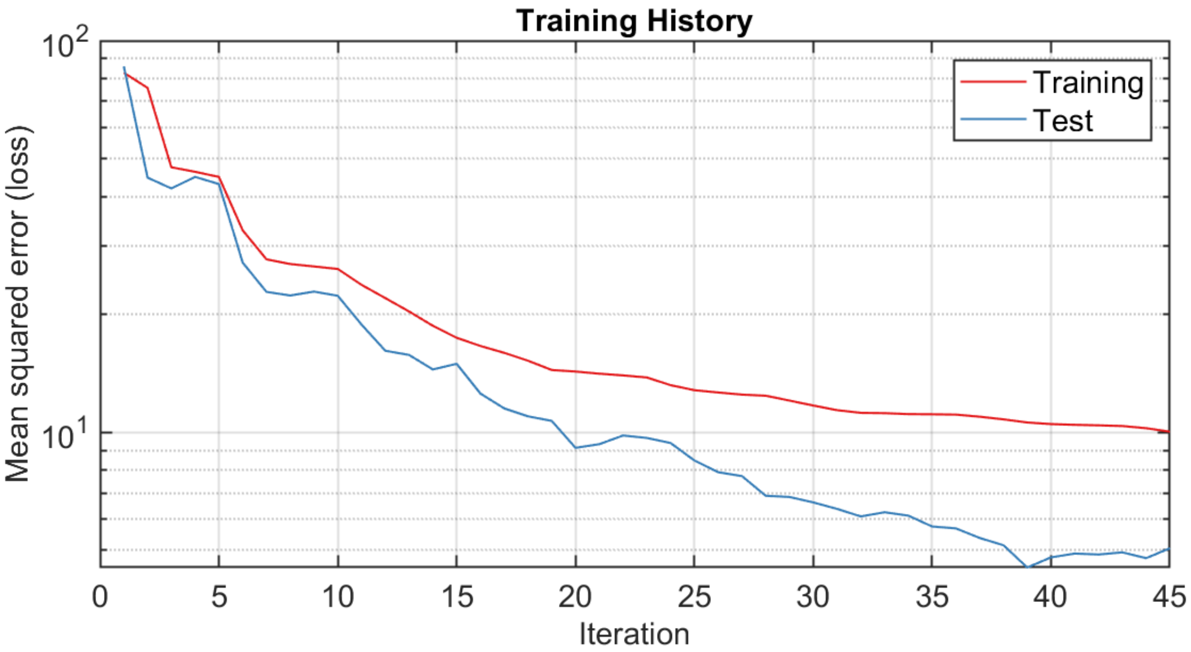

Training data	
Min. value	-52.4010
Median	27.9940
Max. value	52.5140

Training	
Test MSE	4.5217
R-squared	0.9974

5-fold cross-validation	
Max. loss	9.0095
Mean loss	5.8957
Std. deviation	3.1606
Validation RMSE	2.4281

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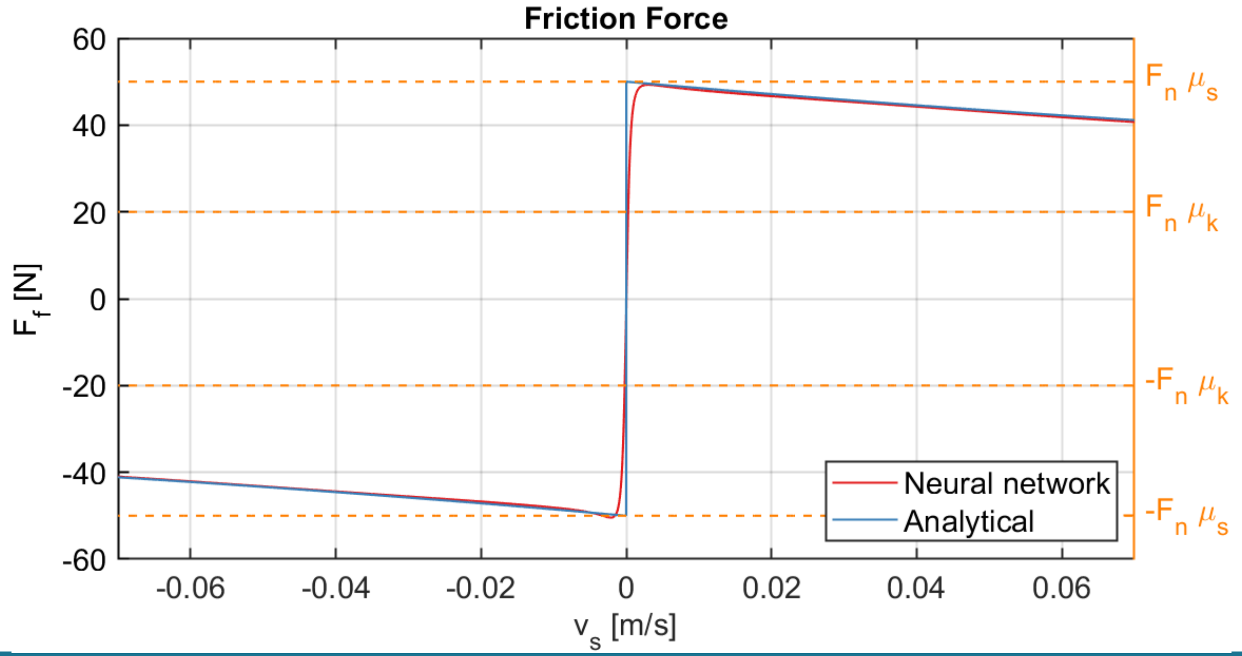
Regression neural network friction model

- Good overall performance



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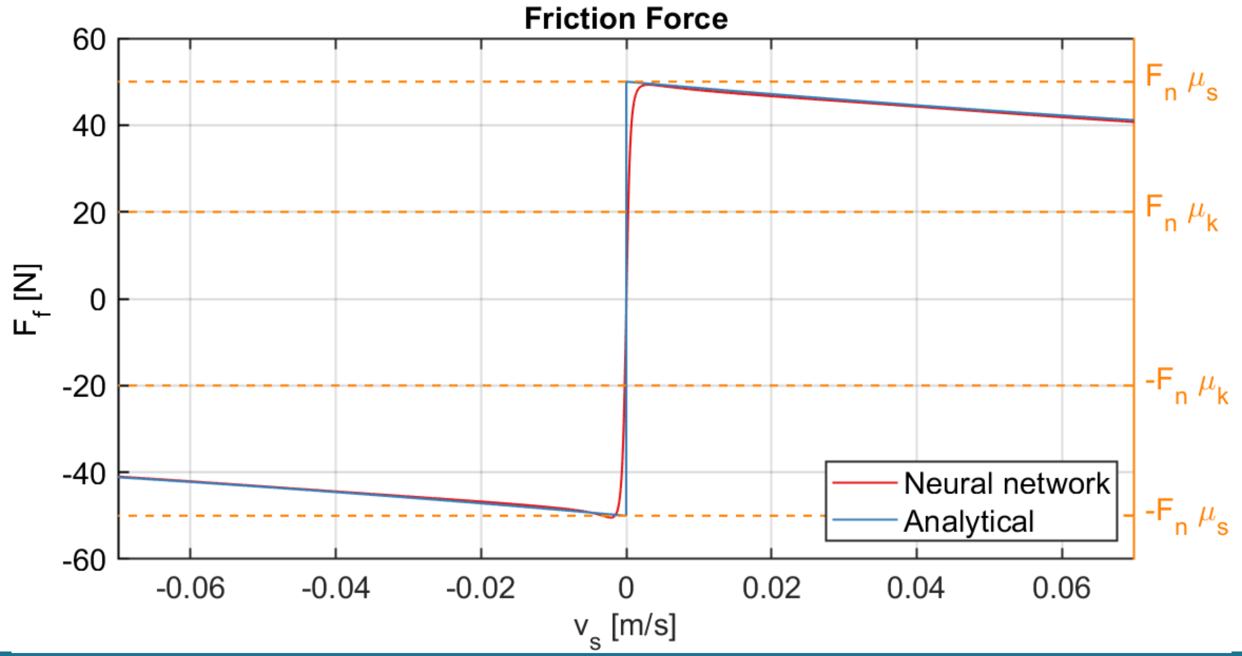
- Discontinuity hard to capture by NN regression model



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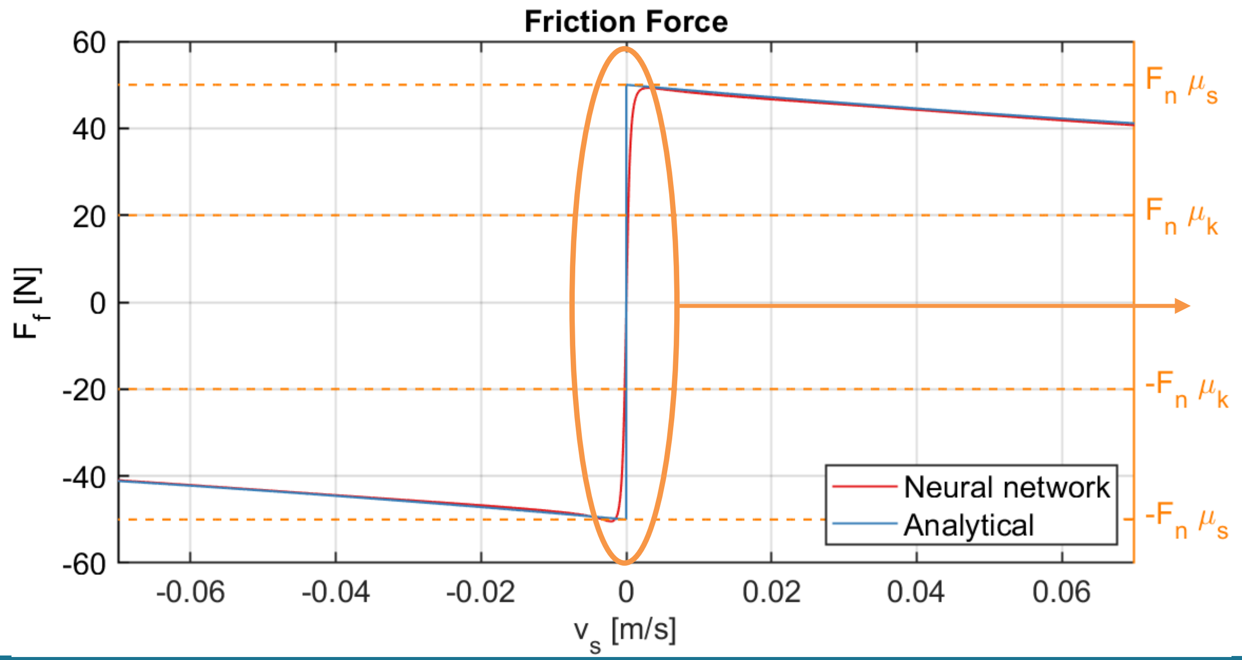
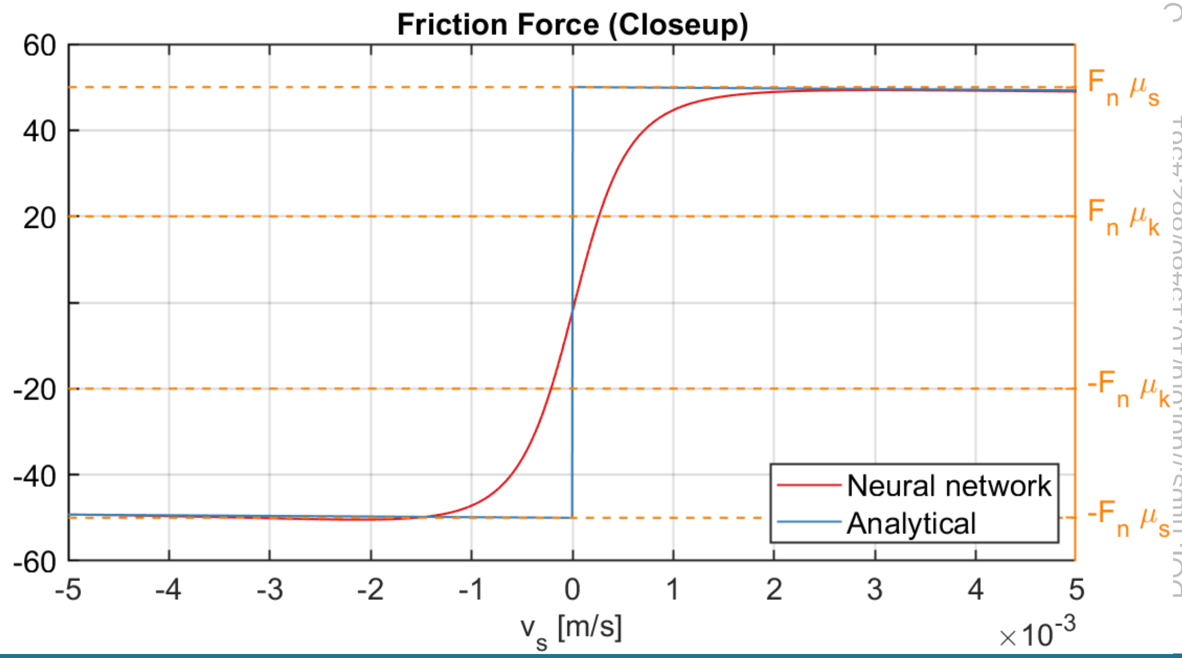
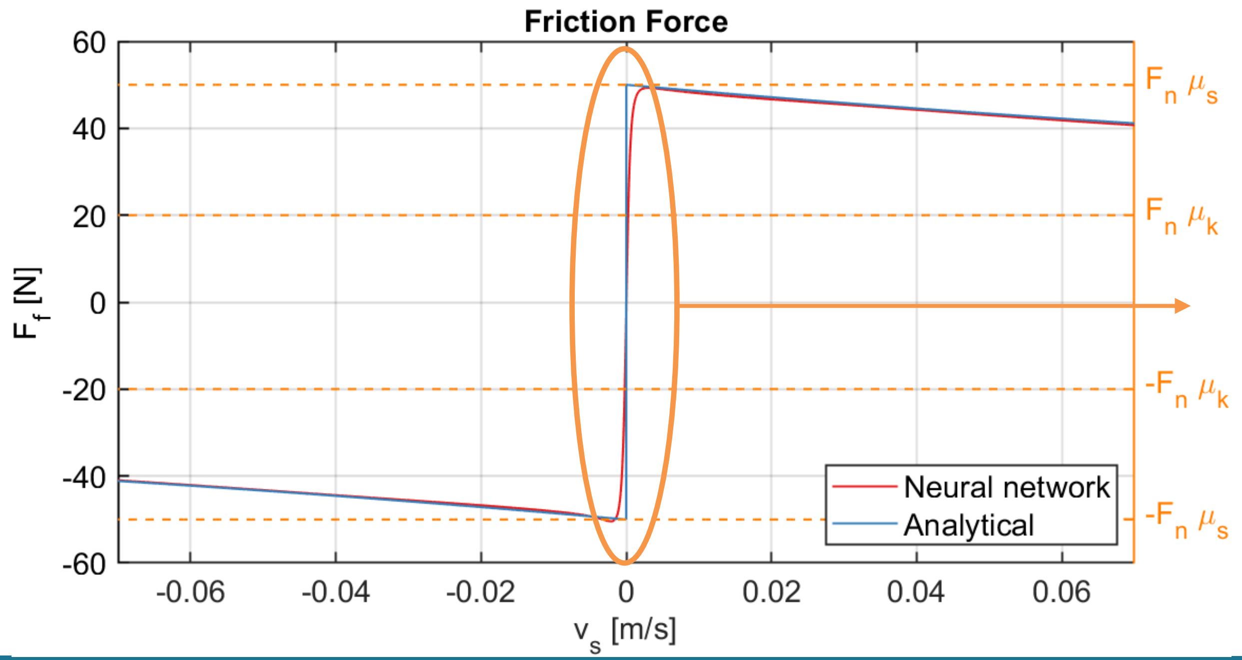
- Jump at the origin is smoothed out

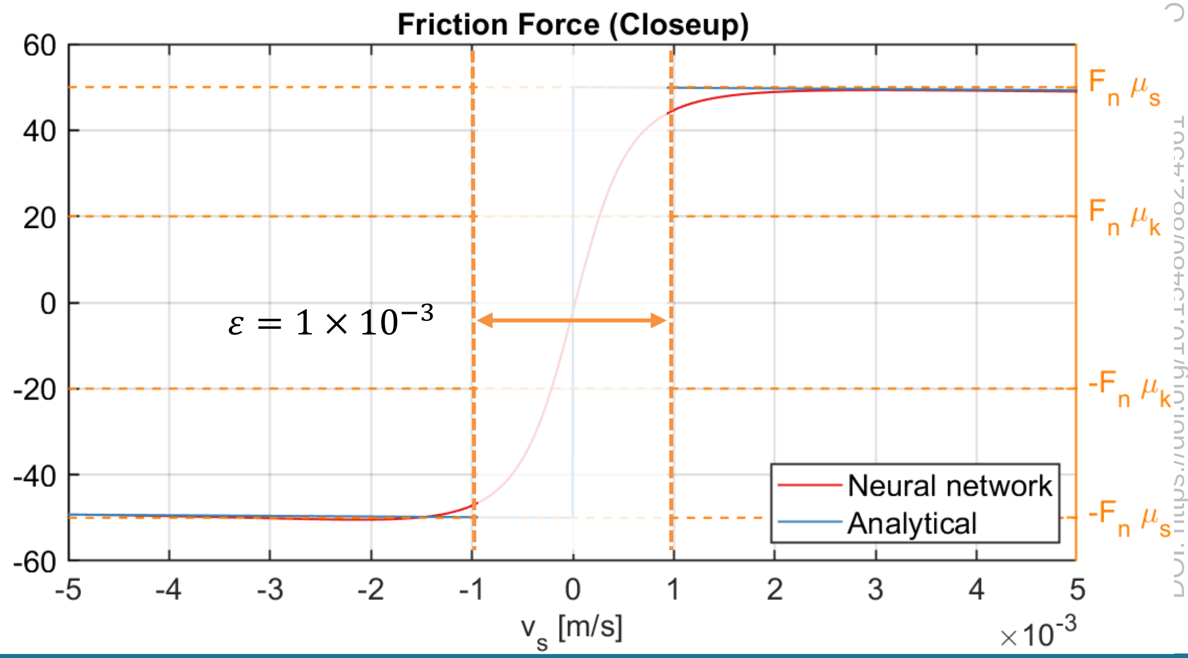




Regression neural network friction model

- Good overall performance
- Discontinuity hard to capture by NN regression model
- Jump at the origin is smoothed out
- Threshold value for sliding velocity ε mitigates this problem





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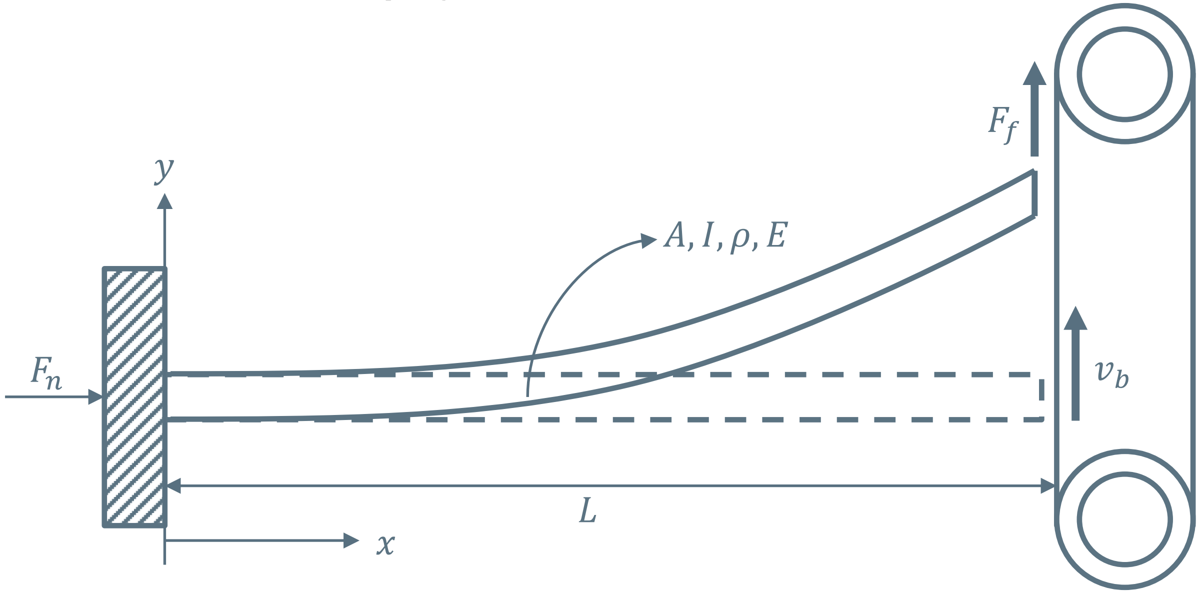

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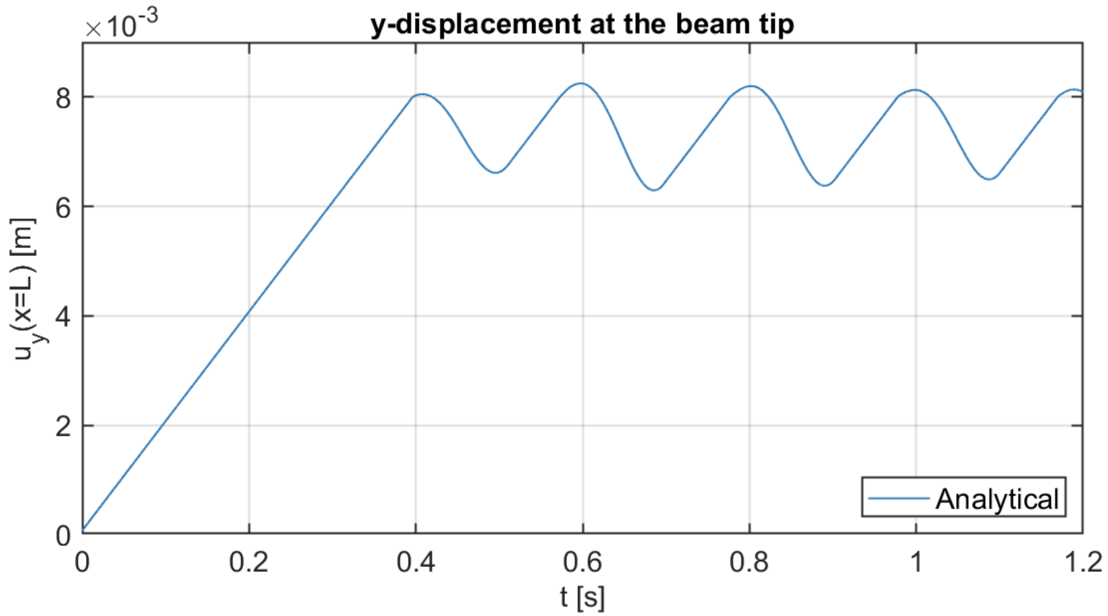
Cantilever beam Finite Element analysis



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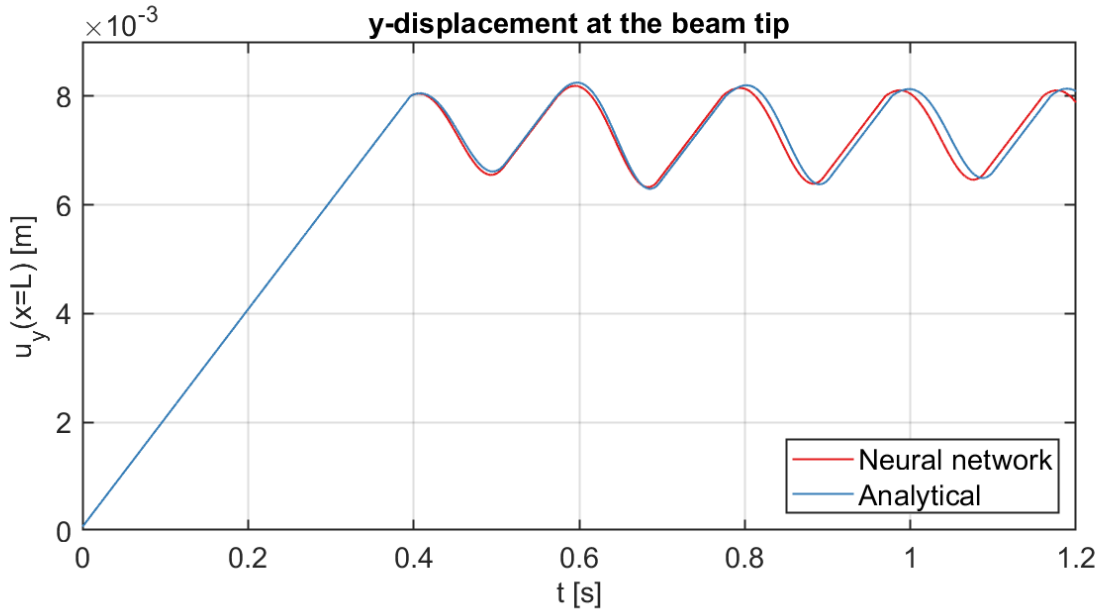

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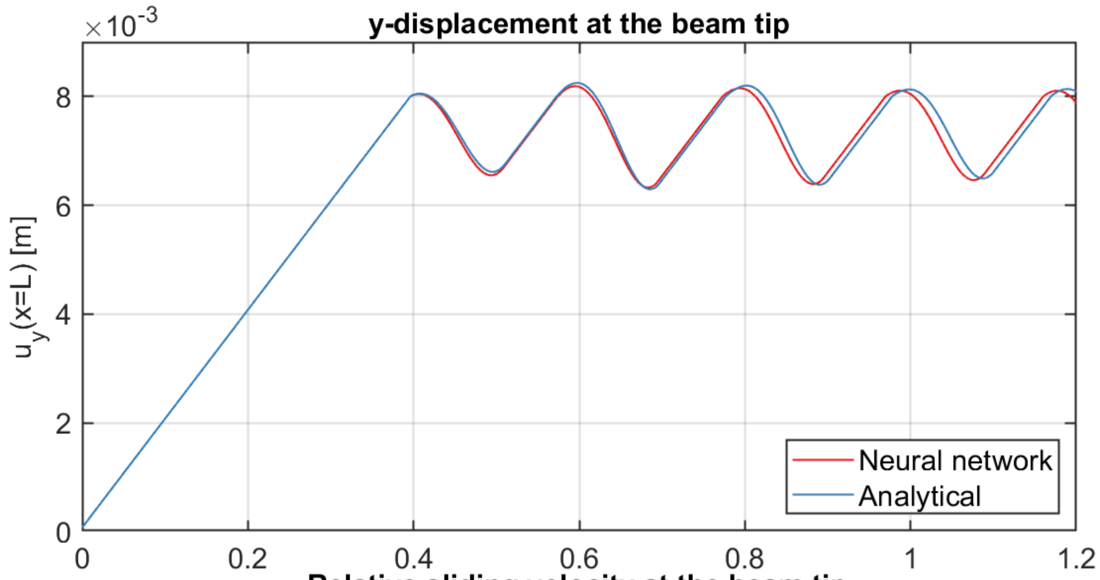

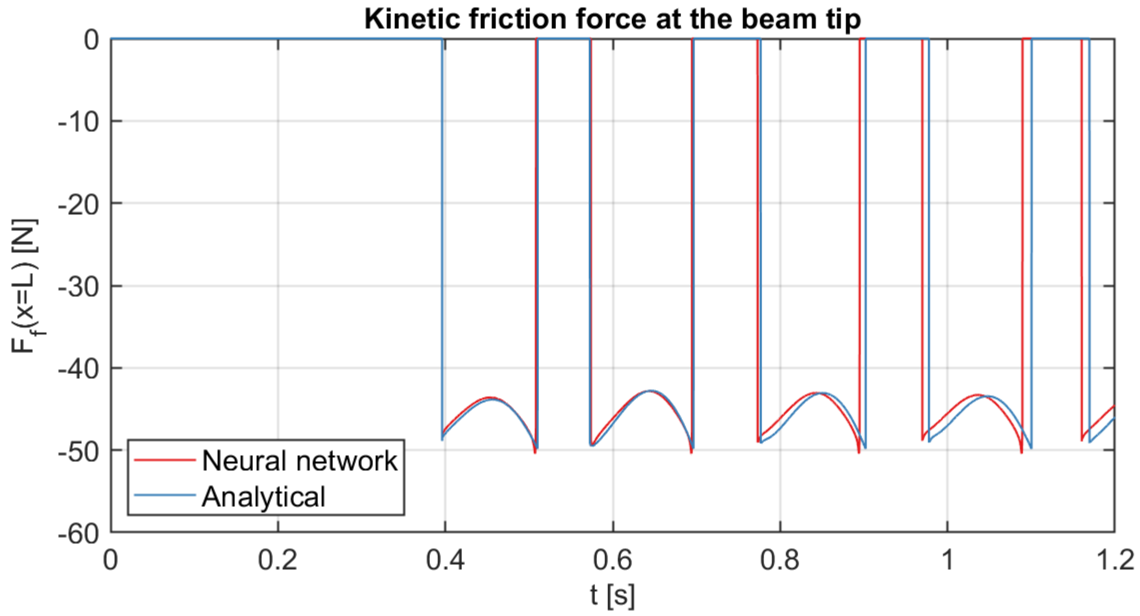

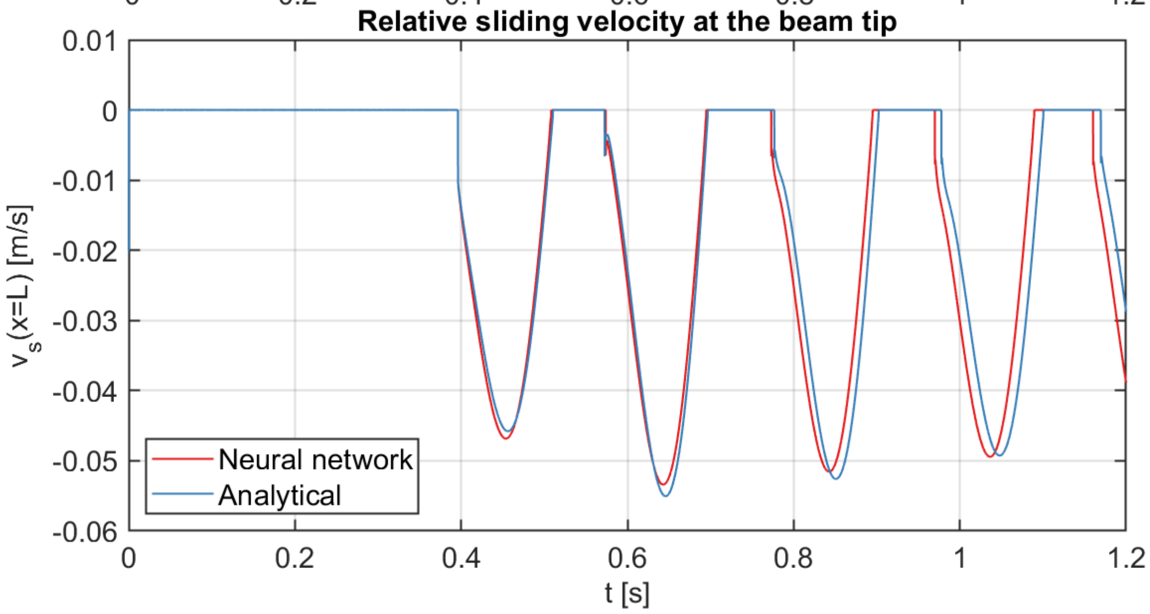

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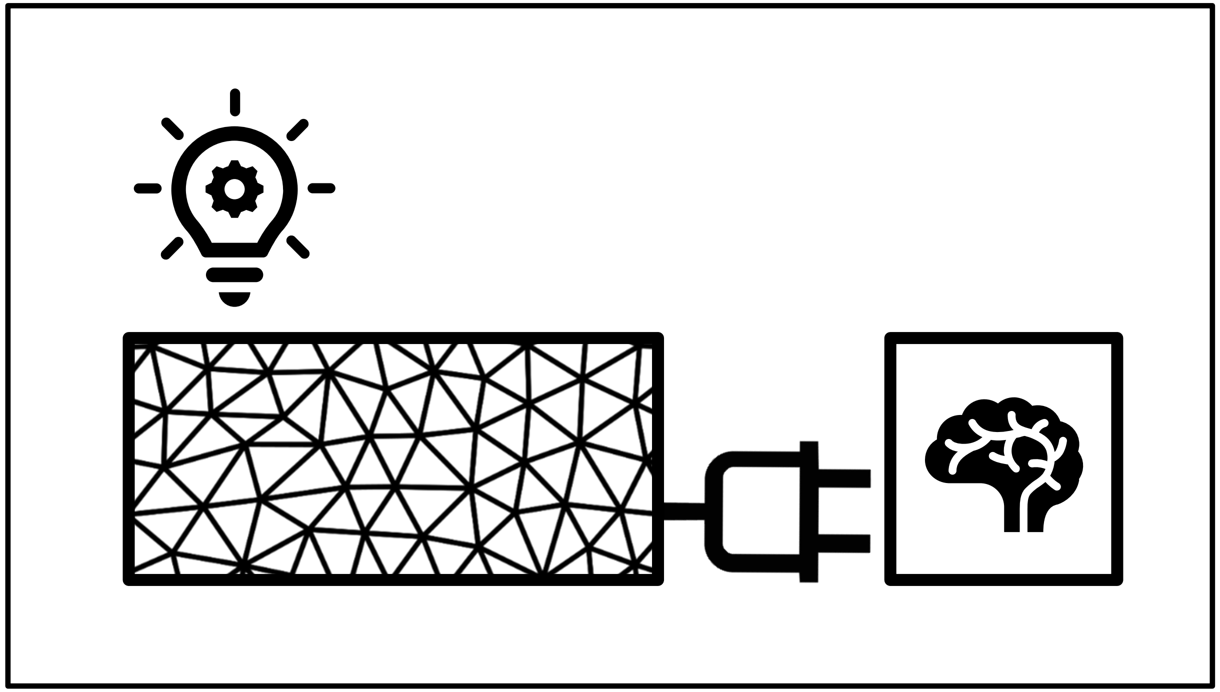
Outlook

- Find better hyperparameters or network architectures
- Introduce physics awareness in the ML model

- Incorporate more features in the friction model
- Leverage data from real measurements

ORCID iD: https://orcid.org/0000-0002-4893-3083
DOI: https://doi.org/10.15480/882.4561

Plug and play!



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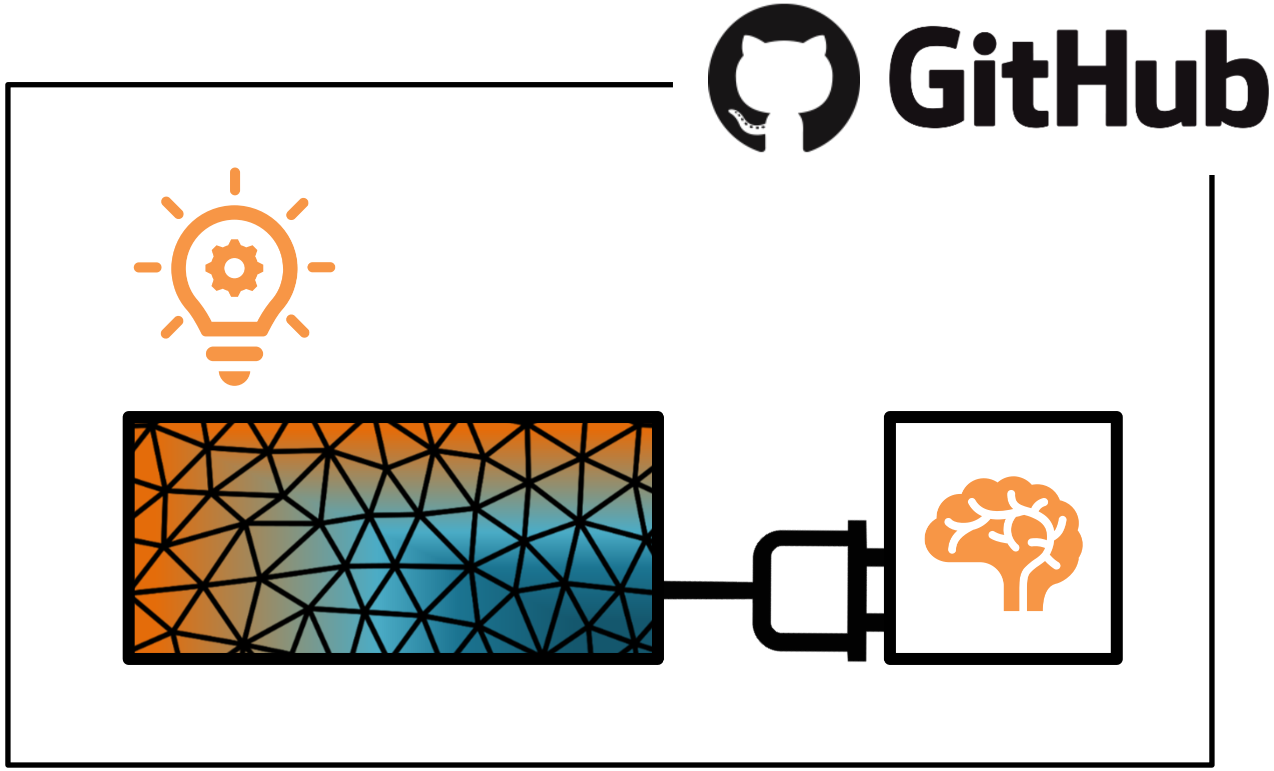

https://github.com/TUHH-DYN/
NeuralNetworkFrictionModel_FEA

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Thank you!

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Parameter values

Cantilever beam model		
Beam length	L	$2\ \mathrm{m}$
Cross-sectional area	A	$0.01\ \mathrm{m}^2$
Moment of intertia	I	$\frac{1}{12} \times 10^{-6}\ \mathrm{m}^4$
Mass density	ρ	$1000\ \frac{\mathrm{kg}}{\mathrm{m}^3}$
Young‘s modulus	E	$2 \times 10^{11}\ \frac{\mathrm{N}}{\mathrm{m}^2}$
Belt velocity	v_b	$0.02\ \frac{\mathrm{m}}{\mathrm{s}}$
Axial load	F_n	$100\ \mathrm{N}$

Computational parameters		
Damping	β	1×10^{-2}
Threshold for sliding velocity	ε	$1 \times 10^{-3} \frac{\mathrm{m}}{\mathrm{s}}$
(Outer) time step size	$\mathrm{d}t$	$1 \times 10^{-4}\ \mathrm{s}$
Abs. solver tolerence		1×10^{-6}
Rel. solver tolerance		1×10^{-3}

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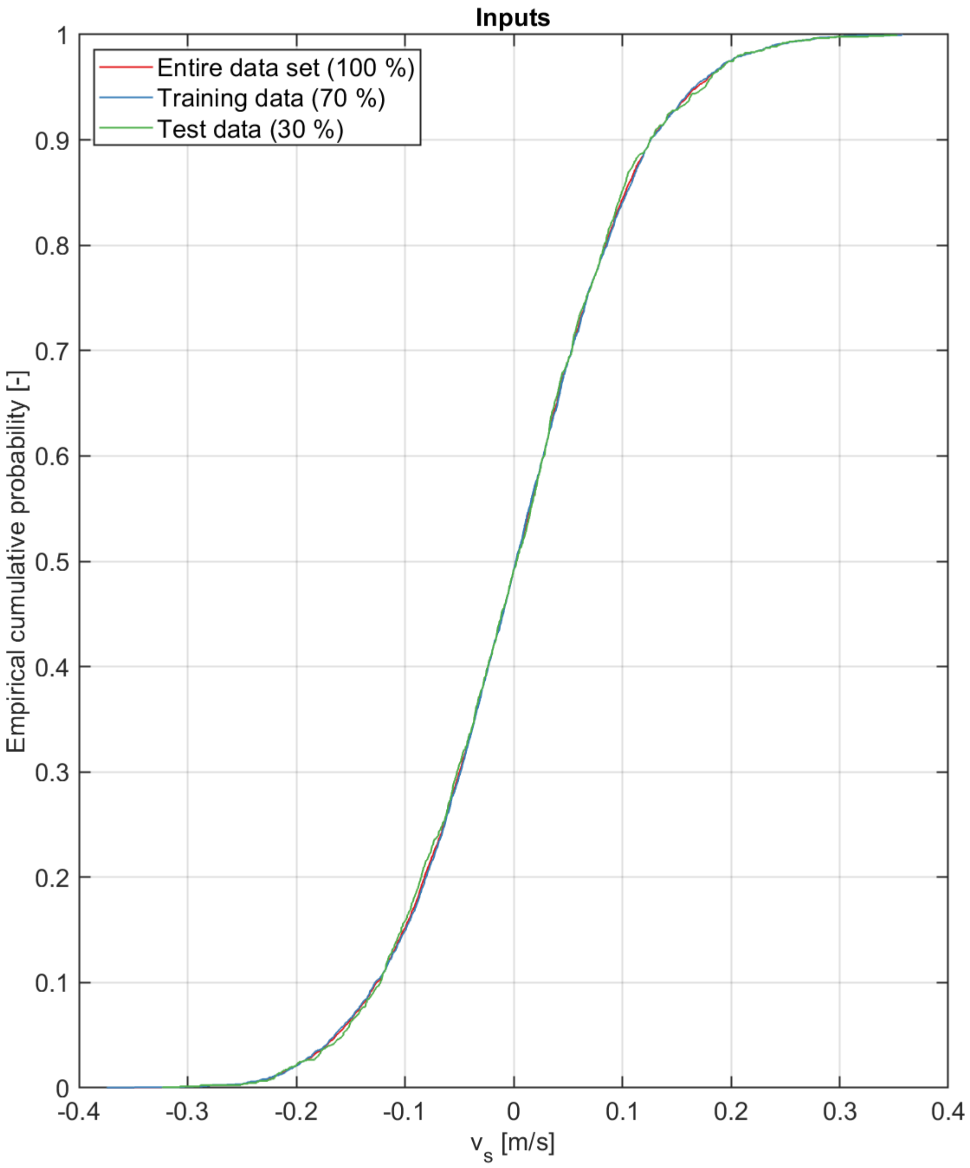
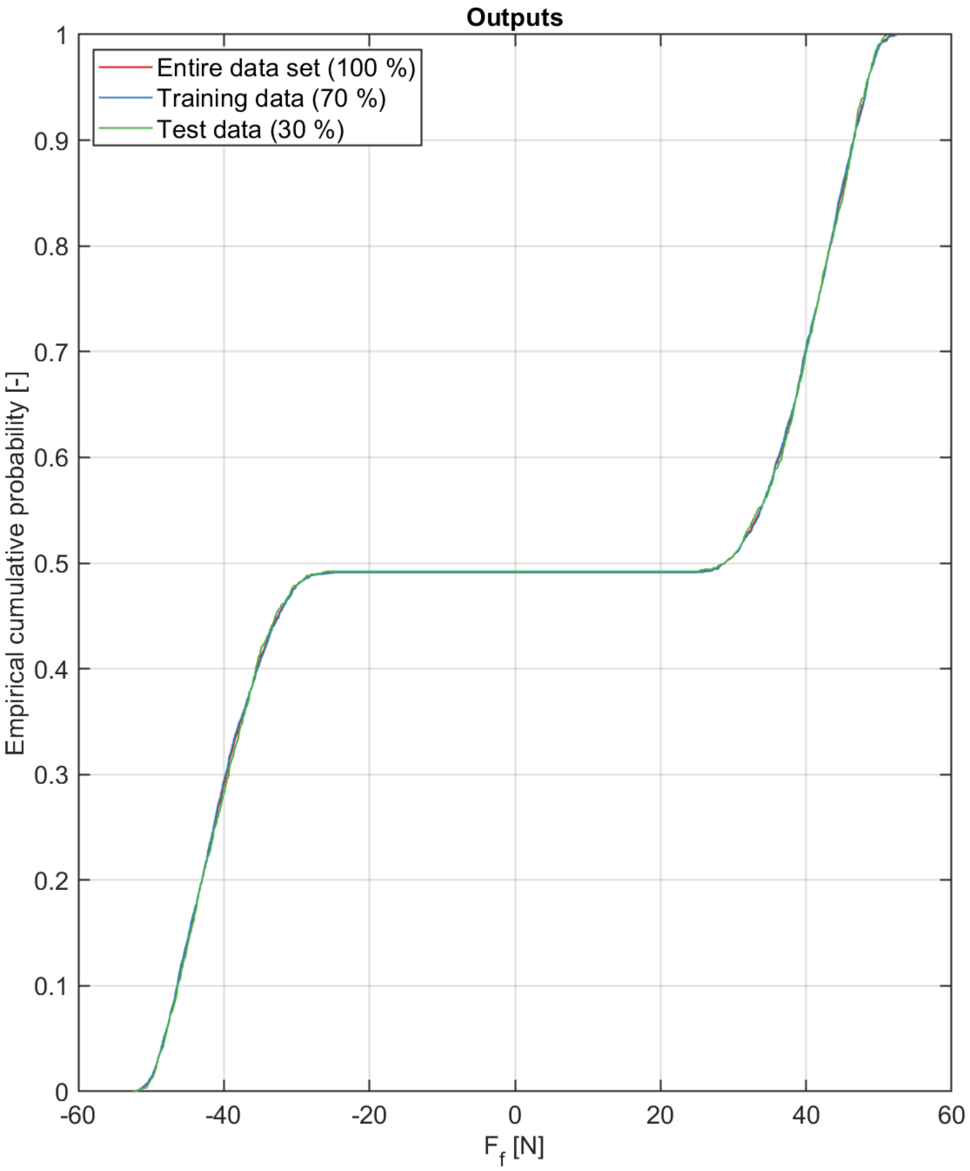
Friction data sampling and partitioning





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