A Long Short Term Memory Network-Based Surrogate Model for Predicting Ductile Fracture

Track: Rising Stars of Mechanical Engineering Celebration & Showcase

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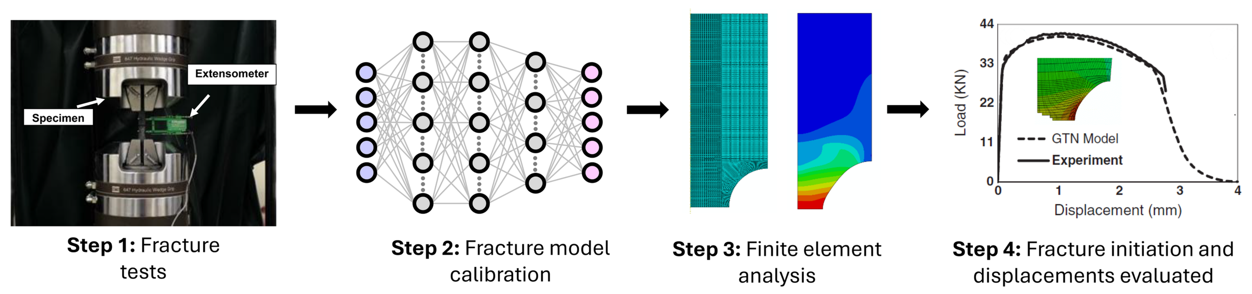
Project Objectives and Goals

Goal: To efficiently automate the prediction of load-displacement behavior until fracture of structural steel.

Objectives: (a) To develop a geometry-specific, data-driven surrogate model to predict load-displacement behavior and ductility of cylindrically notched metal specimens; (b) To validate the proposed data-driven surrogate model by comparing its predictions with experimental fracture data.

Background

Conventional fracture prediction



GTN fracture model

GTN Equations

$$\phi(\sigma_e,\sigma_h,f^*,\sigma_y)=\left(\frac{\sigma_e}{\sigma_y}\right)^2+2f^*q_1\cosh\left(q_2\frac{3\sigma_h}{2\sigma_y}\right)-1-q_3{f^*}^2=0 \quad (1)$$

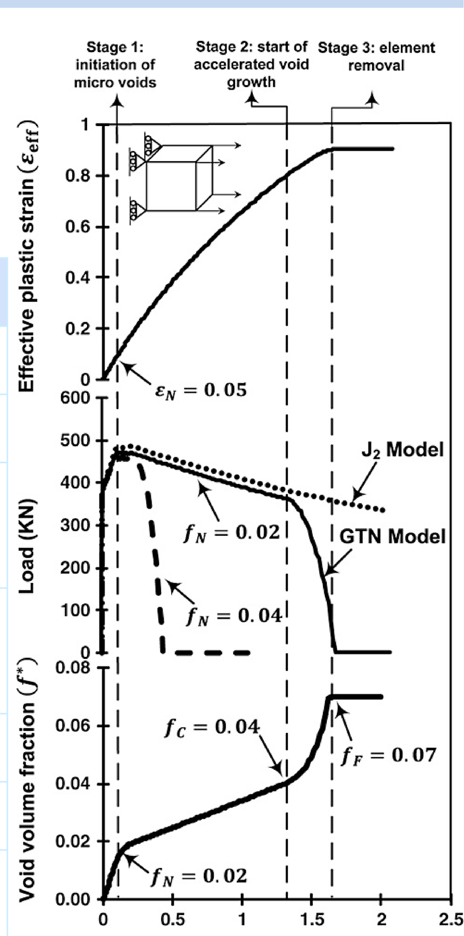
$$f^*=\begin{cases} f, & f\le f_c \\ f_c+K(f-f_c), & f_c<f<f_F \end{cases} \quad (2)$$

$$A=\frac{f_N}{s_N\sqrt{2\pi}}\exp\left(-\frac{1}{2}\left(\frac{\varepsilon^p_{eff}-\varepsilon_N}{s_N}\right)^2\right) \quad (3)$$

GTN Parameters

q_1, q_2, q_3	Void interaction parameters
f_o	Initial void volume fraction
f_N	Void volume fraction at nucleation
f_c	Void volume fraction at coalescence
f_F	Final void volume fraction
ϵ_N	Mean nucleation strain
s_N	Std. dev. of nucleation strain

GTN Performance



- Fracture tests are time and resource-intensive.
- A 2D axisymmetric model with 56,319 linear quadrilateral elements with reduced integration requires 8 hours of simulation time using 4 CPU cores in ABAQUS (Explicit).

Research Question: Is it possible to develop a data-driven surrogate model to reduce computation costs of the finite element analysis of test specimens undergoing ductile fracture?

Methodology

Step 1	Step 2	Step 3	Step 4	Step 5
Calibration of fracture model (GTN model)	Generate training data using virtual uniaxial tension test specimens	Develop a LSTM/Bi-LSTM based surrogate model	Train the surrogate model using the training data	Validate the surrogate model using uniaxial tension tests

Step 1: GTN parameters [1]

q_1	1.5	Void interaction parameters
q_2	1.0	
q_3	2.25	
f_o	0	Initial void volume fraction
f_N	0.02	Void volume fraction at nucleation
ϵ_N	0.45	Mean nucleation strain
s_N	0.05	Std. dev. of nucleation strain
f_c	0.03	Void volume fraction at coalescence
f_F	0.5	Final void volume fraction

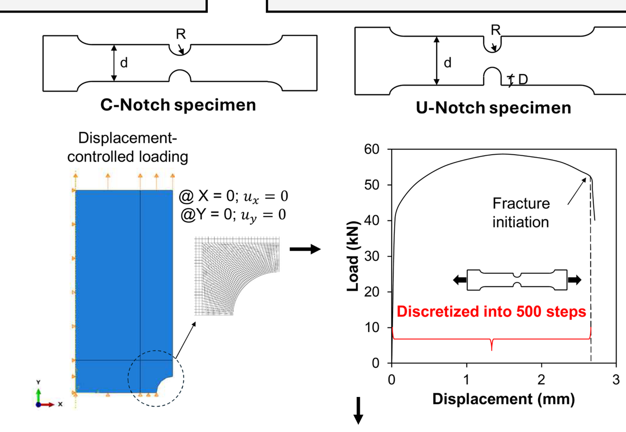
Step 2: Data generation

Calibration

- 42 virtual C-notch and U-notch specimens.
- Specimen dia: 15 to 25 mm
- Notch radii: 0.5 to 2 mm

Validation

- 10 C-notch and U-notch specimens.[2,3]
- Specimen dia: 12 to 16 mm
- Notch radii: 0.5 to 3 mm

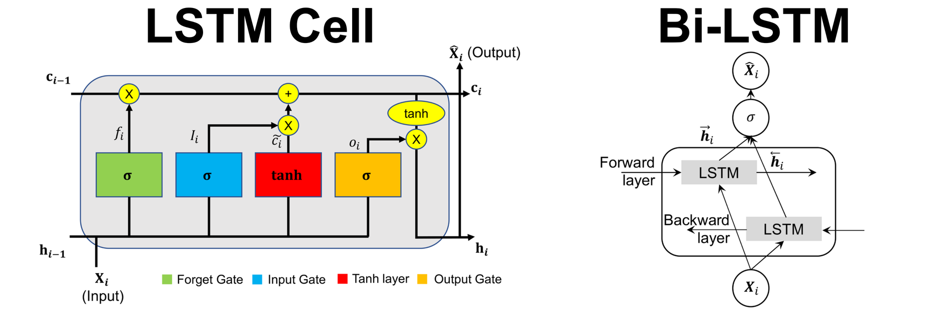


Load step	Displacement	Load
1	$u_f/500$	l_1
2	$u_f/250$	l_2
3	$3u_f/500$	l_3
⋮	⋮	⋮
500	u_f	l_{500}

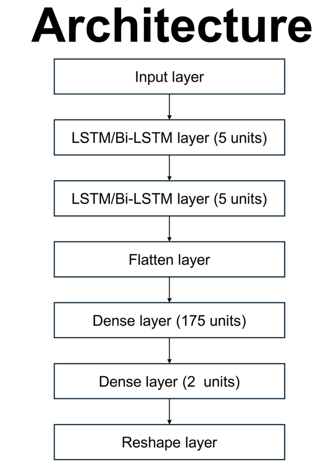
- Ductile fracture is a history-dependent process.
- Hypothesized load displacement until fracture as time series data.

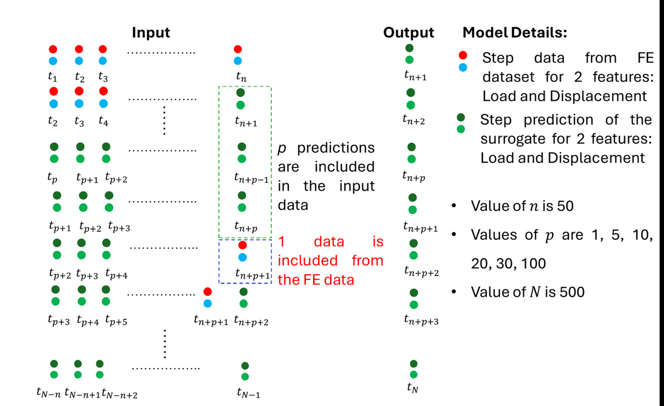
Step 3: Surrogate model

LSTM Cell **Bi-LSTM**



Architecture **Prediction scheme**



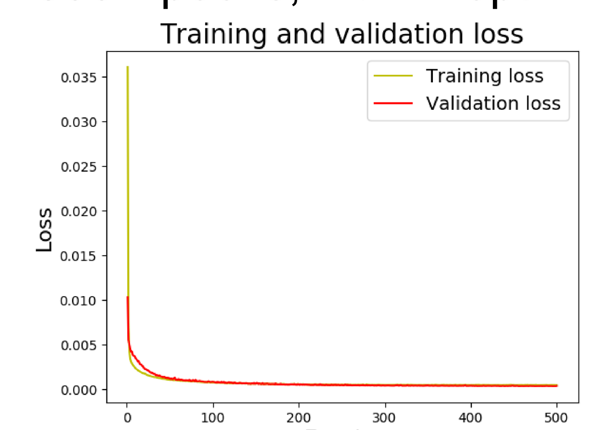


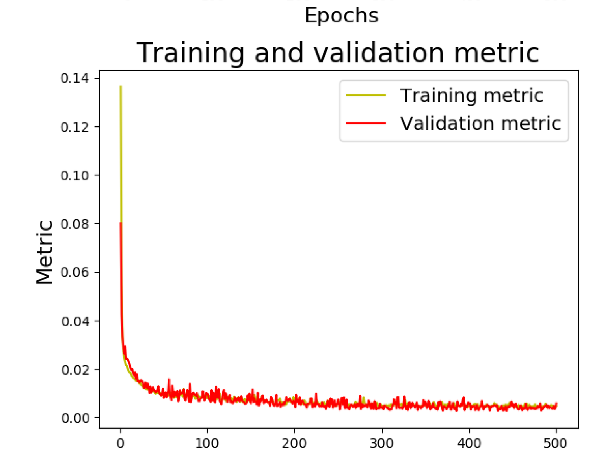
- LSTM can handle long-term dependency.
- Past events influence the present and future events.

Results

Step 4: Model training

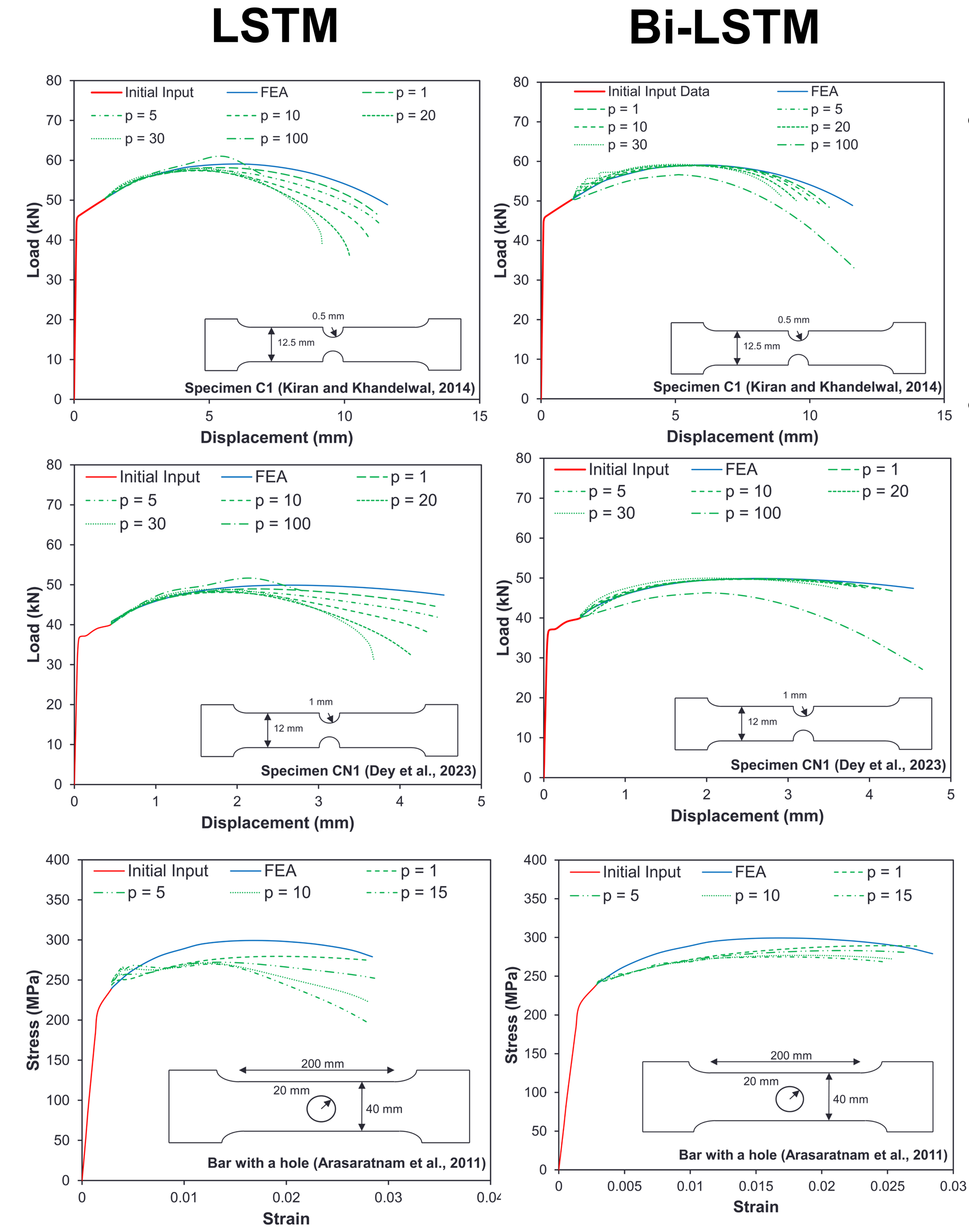
- Cost function: Mean squared error (MSE)
- Metric: Mean absolute error (MAE)
- Training : Validation = 80 : 20
- MSE: 4×10^{-4} ; MAE: 4×10^{-3}
- 500 Epochs; ADAM optimizer





Step 5: Model validation

LSTM **Bi-LSTM**



- Bi-LSTM surrogate model simulates better post-peak softening and ductility for $p \le 30$.
- LSTM surrogate model yields an acceptable load-displacement response until $p = 20$.

Limitation: The proposed surrogate model is geometry and material-specific but can be extended to other geometries and materials.

Conclusions

1. Surrogate models can be trained by treating load-displacement data as a time series to predict fracture specimens' mechanical behavior and ductility.
2. The surrogate models capturing both forward and backward trends are more accurate.
3. The maximum number of steps that can be predicted simultaneously without significantly compromising the accuracy is 20.
4. This framework can be extended for other material systems and loading scenarios.
5. ***Limitations:*** a) Surrogate models are geometry and material-specific; b) They cannot handle variable length sequences.

Future Studies / Recommendations

1. Increase the number of virtual specimens used to train the surrogate model.
2. Generalize the surrogate model by adding new geometries and materials to the training data.
3. Add physically meaningful mathematical constraints to prevent pre-peak load overshooting in the load-displacement prediction.
4. Extend this framework to other geometries and metals.
5. Improve the post-peak and fracture prediction ability.
6. Incorporate other plasticity and fracture models for better material behavior simulation.

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