ENGINEERING MECHANICS INSTITUTE 2025 CONFERENCE (EMI 2025)

MATERIAL AGNOSTIC DATA-DRIVEN GURSON-TVERGAARD-NEEDLEMAN MODEL FOR DUCTILE FRACTURE

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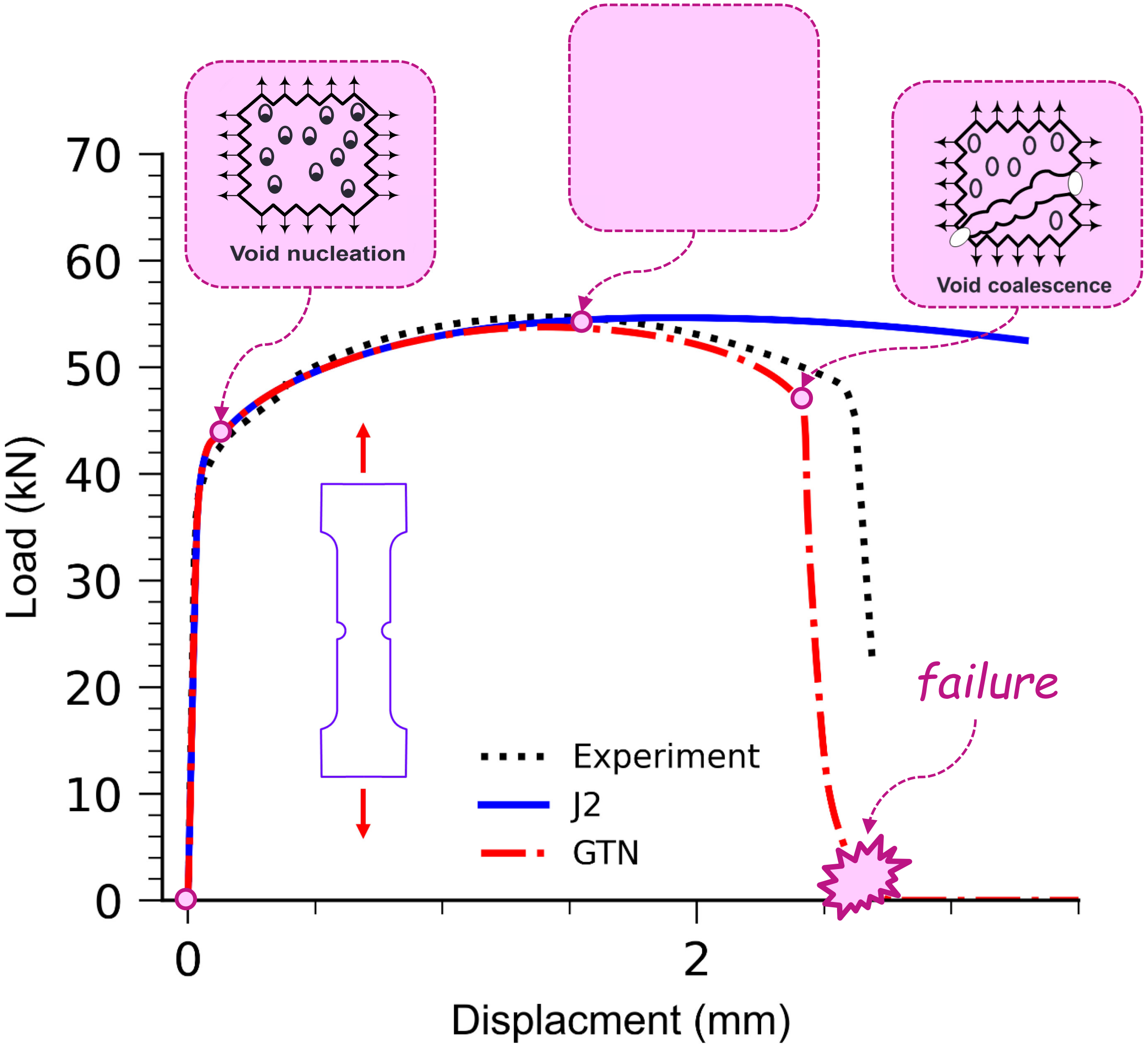
Ductile Fracture: Gurson-Tvergaard-Needleman (GTN) model



- GTN model has both the deviatoric and hydrostatic stress dependence unlike the J_2 plasticity model.
- Simulates damage by tracking a single damage variable – void volume fraction.

Important Observation: Softening due to void growth is not significant in high strength low alloy steels.

Research Question: Is it possible to predict DF without material softening while leveraging the predictive power of GTN Model?

stress triaxiality $\eta = \sigma_h/\sigma_{eq}$

Objectives

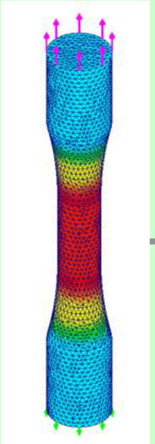
- To develop a fast-to-compute, data-driven approach for high-fidelity prediction of fracture initiation in ductile metals.

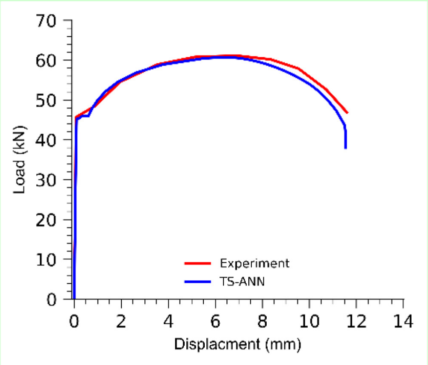
- To validate the proposed material agnostic approach by comparing its predictions to experimental fracture data for steel and aluminum.

Overall Methodology

Stage 1: Fracture data Generation

Stage 2: Training and configuration of Neural Network Model

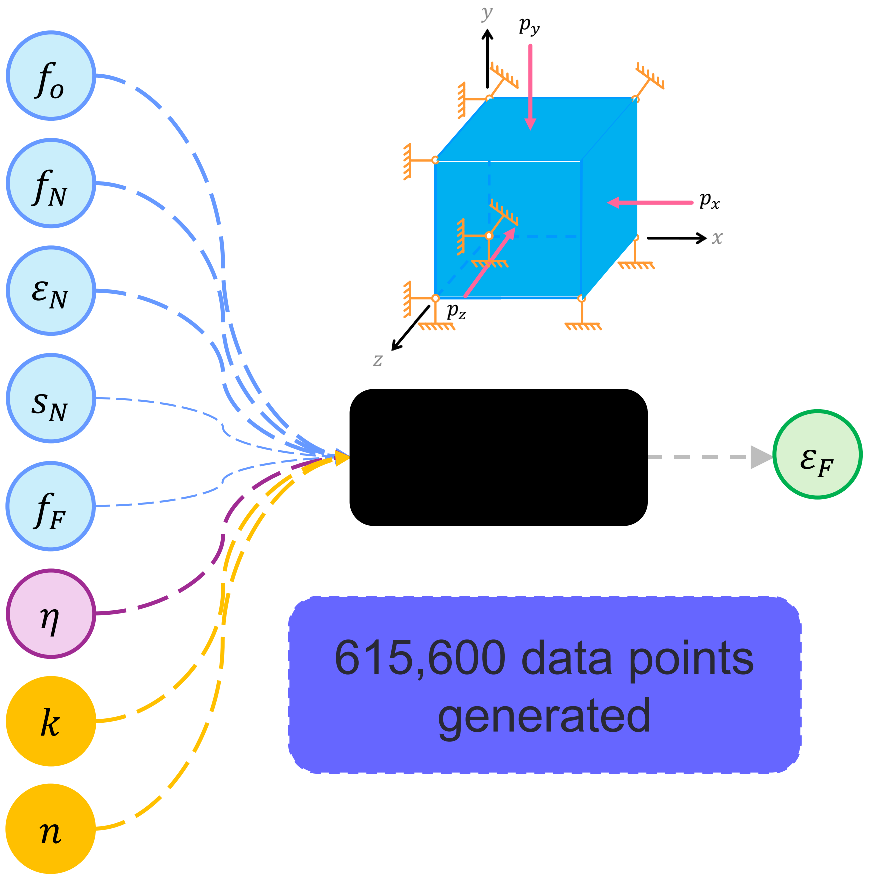




FEM Analysis

Stage 3: Prediction of fracture using TS-ANN model

Stage 1 – Generation of fracture data

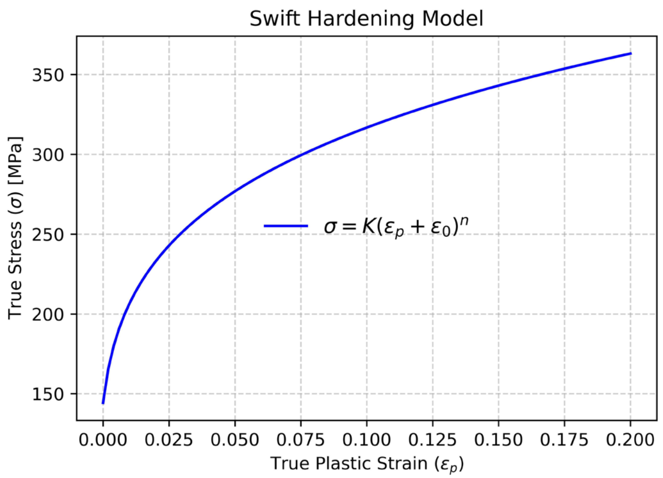


GTN Parameters	Min.	Max.	Inc.	Level
Initial void volume fraction (f_o)	0.0	0.008	0.002	5
Nucleation void volume fraction (f_N)	0.002	0.01	0.002	5
Mean nucleation plastic strain (ε_N)	0.1	0.5	0.1	5
Std. deviation of nucleation strain (s_N)	0.025	0.01	0.025	5
Failure void volume fraction (f_F)	0.01	0.05	0.005	10
Stress triaxiality (η)	0.33	2.0	0.25	9

Hardening Parameters	Min.	Max.	Inc.	Level
Strength coefficient (k)	600	1200	200	4
Strain hardening exponent (n)	0.1	0.3	0.05	5

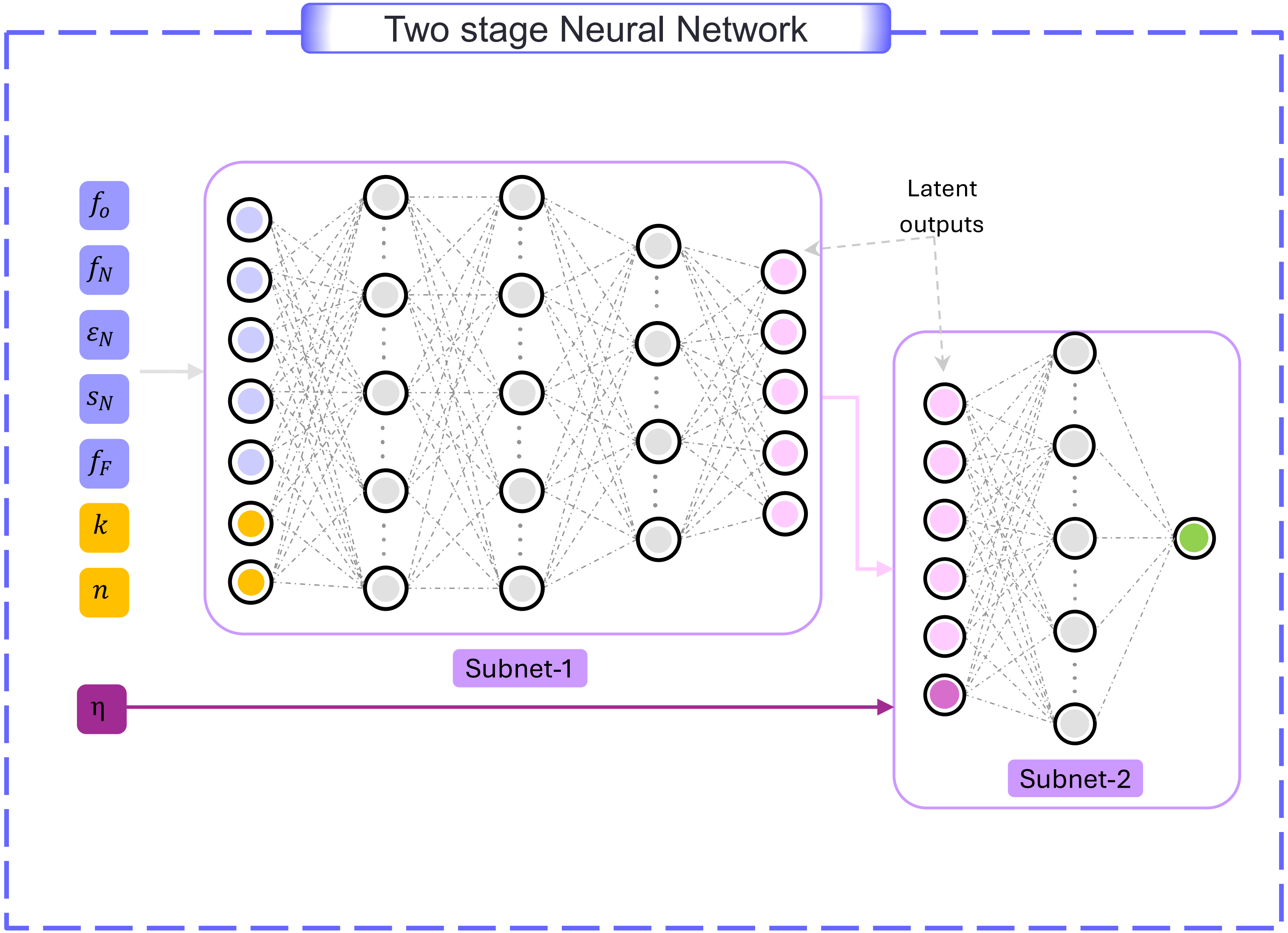
- Negative x, y and z are constrained and positive x, y and z are applied with load.
- p_y and p_x are calculated from triaxiality (η) with prescribed p_z.
- Modelled in Abaqus standard using porous plasticity option

Why Swift Hardening?



Material	k	n	ε_o	Use
Mild Steel (AISI 1018)	600	0.22	0.005	General-purpose construction
Dual-Phase Steel (DP600)	780	0.20	0.01	High strength, auto-grade
Stainless Steel (304)	1100	0.45	0.002	Piping
Titanium Ti-6Al-4V	950	0.15	0.003	Pressure vessels
Nickel Alloy (Inconel 718)	1200	0.25	0.005	Jet engines, Turbines
Aluminum 2024-T351	500	0.15	0.002	Common aerospace alloy

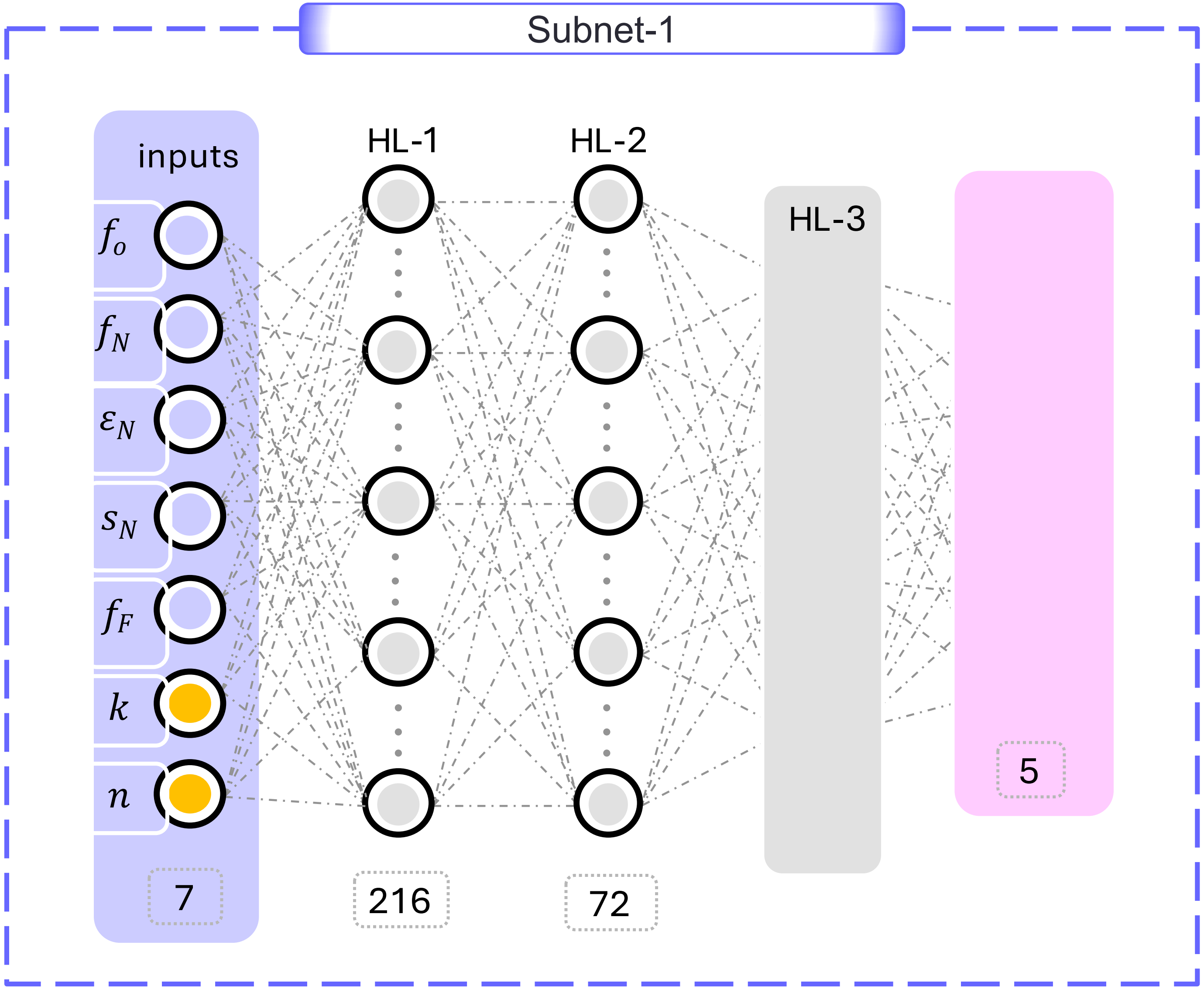
Stage-2 – Training and configuration of neural network model



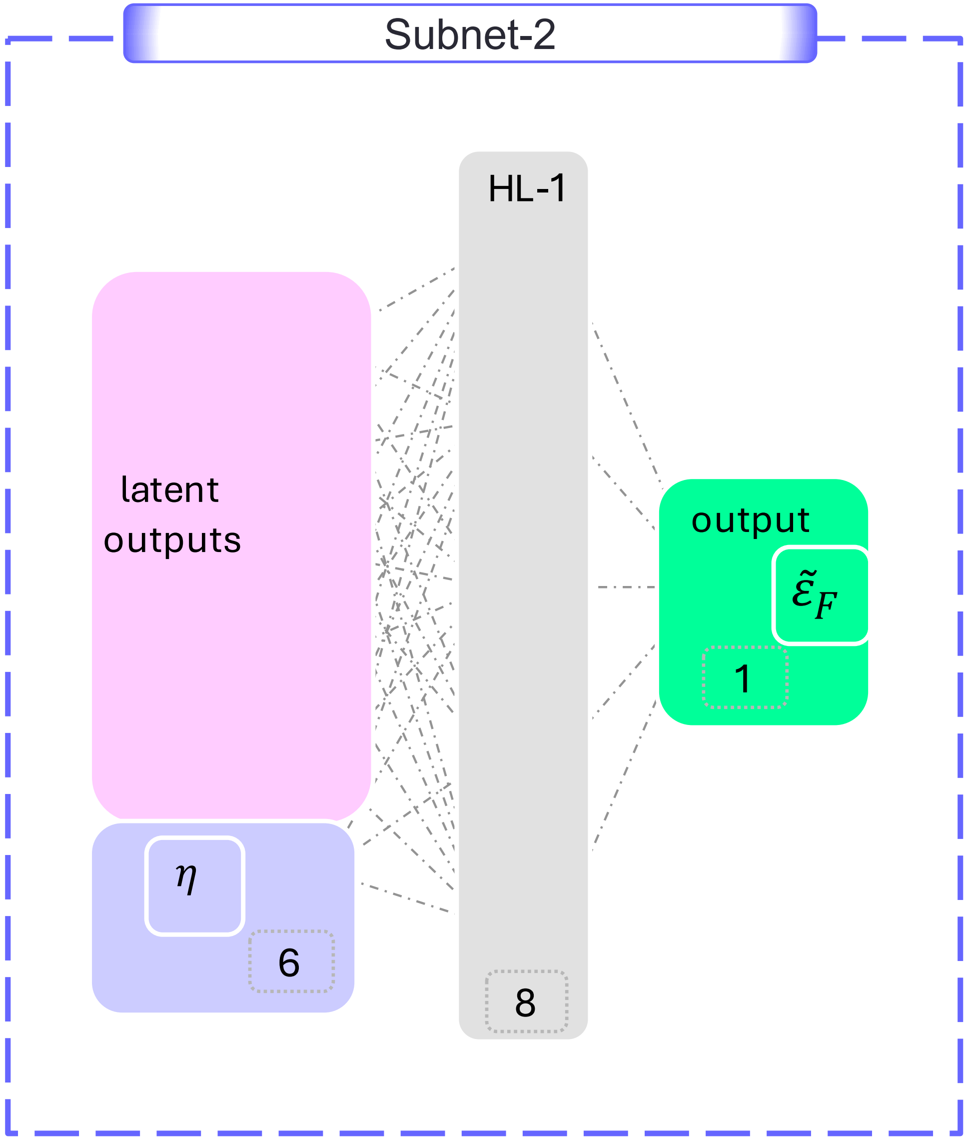
- Larger Subnet-1 used only at the start of the analysis
- Smaller Subnet-2 used at each GQ point at each time step during the analysis
- Significant reduction of computational time

40,000 floating point operations reduced to **40** per GQ per time step

Stage-2 – Configured Network – Subnet-1



Attributes	Subnet-1
No. of input features	7
No. of outputs	5
No. of hidden layers (HL)	3
Activation function for hidden layers	ELU
Activation function for output layer	ELU
No. of neural network parameters	19,299

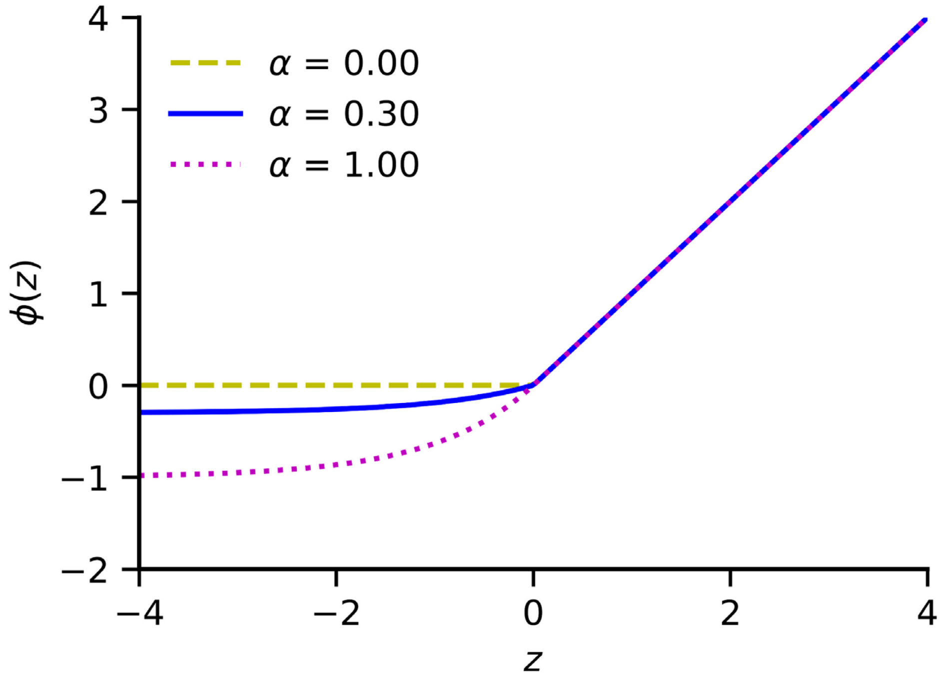


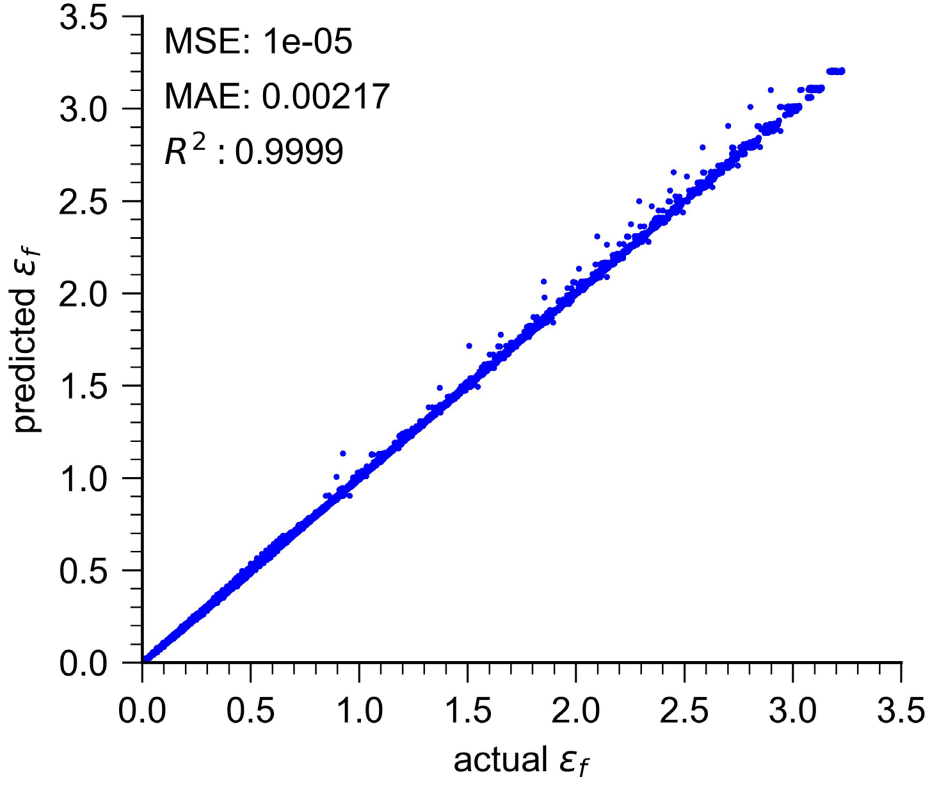
Property	Subnet-2
No. of input features	6
No. of output features	1
No. of hidden layers (HL)	1
Activation function for hidden layers	ELU
Activation function for output layer	ELU
No. of neural network parameters	65

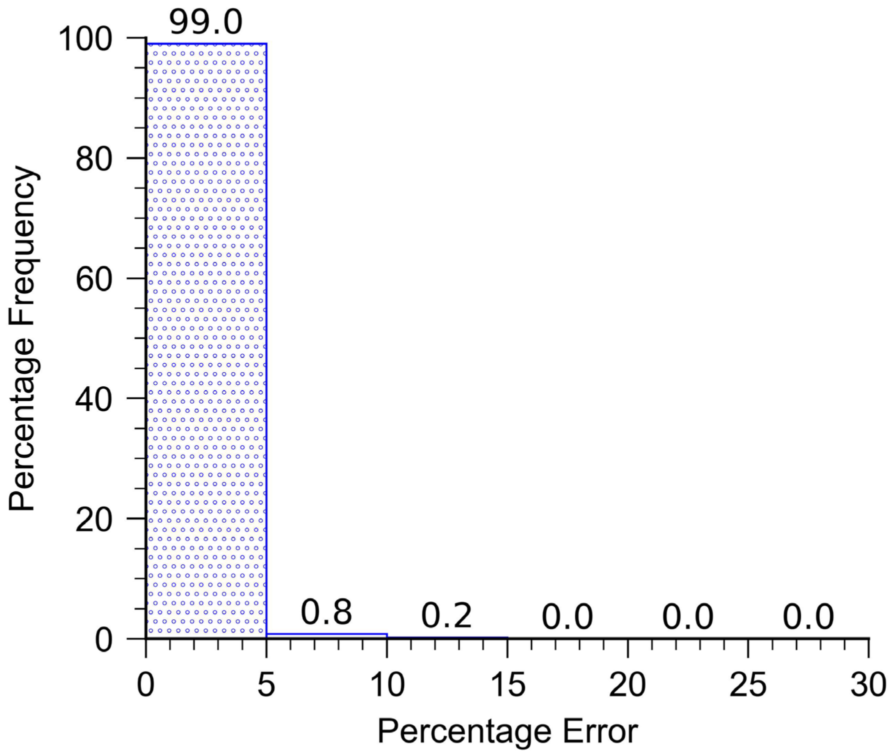
Stage-2 – ELU Activation function

- No gradient saturation
- Faster learning because of no positive bias shift
- Standard value of $\alpha = 1$ is used

ELU activation function

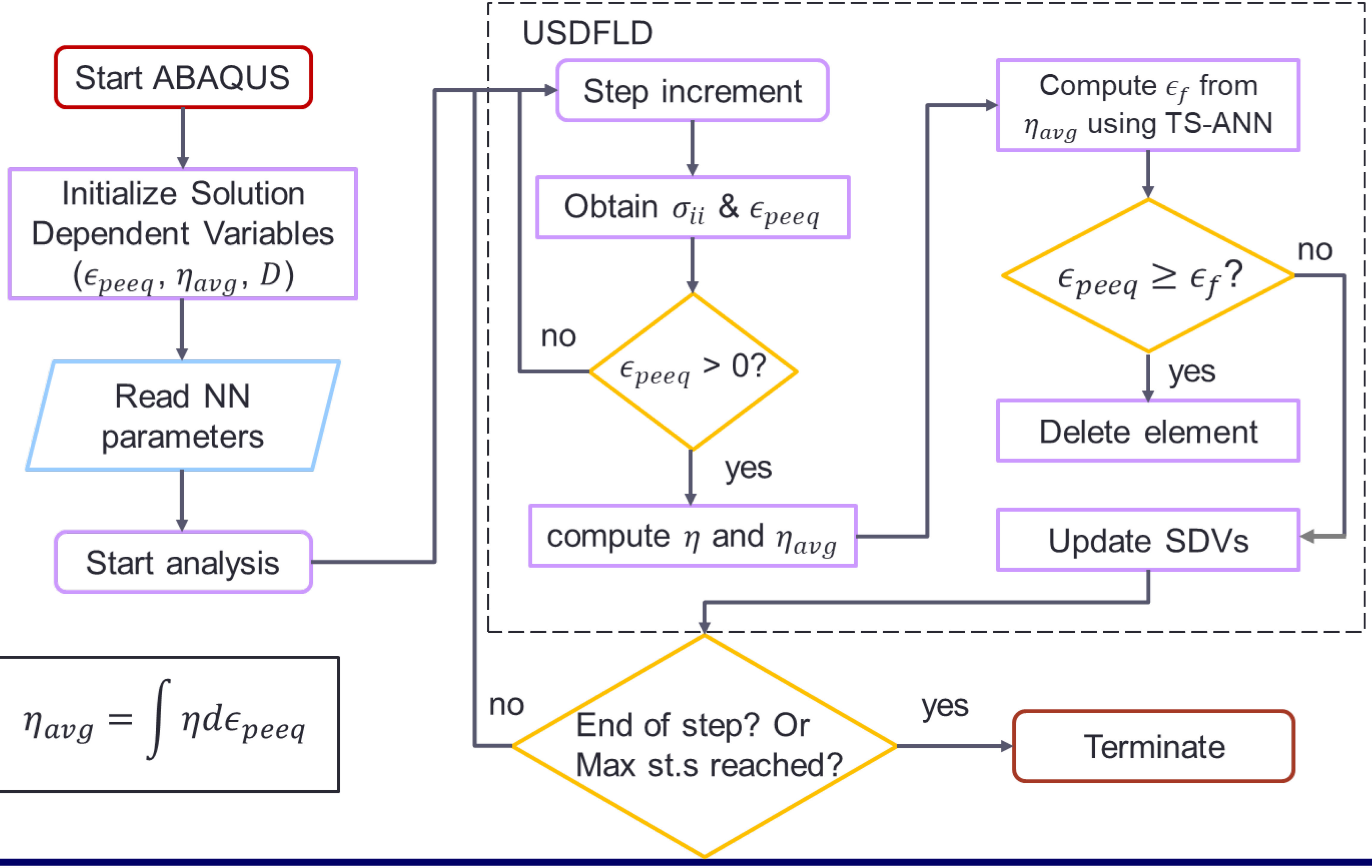






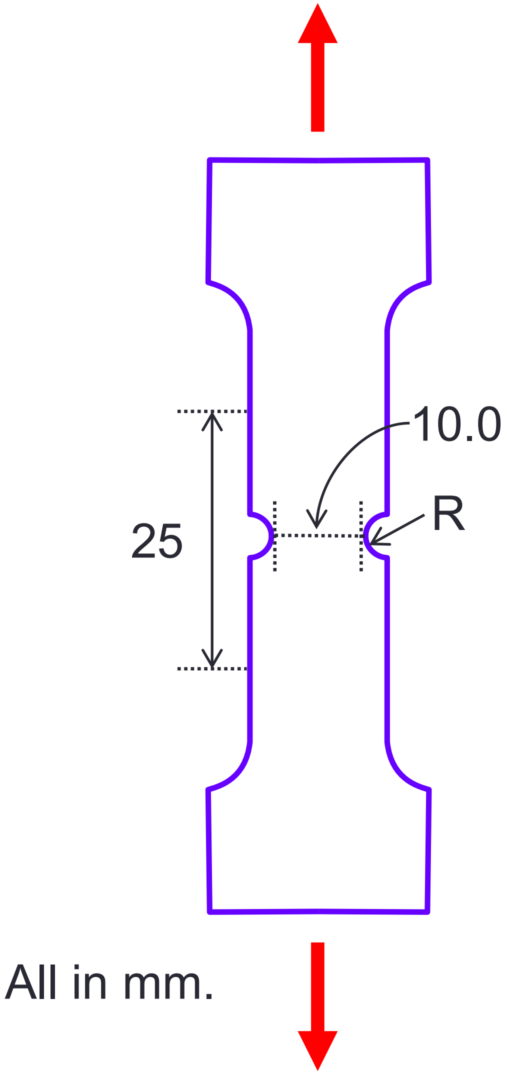
Only 1.0% data exceeds 5% error

Stage 3: Prediction of fracture using TS-ANN model – FEM integration

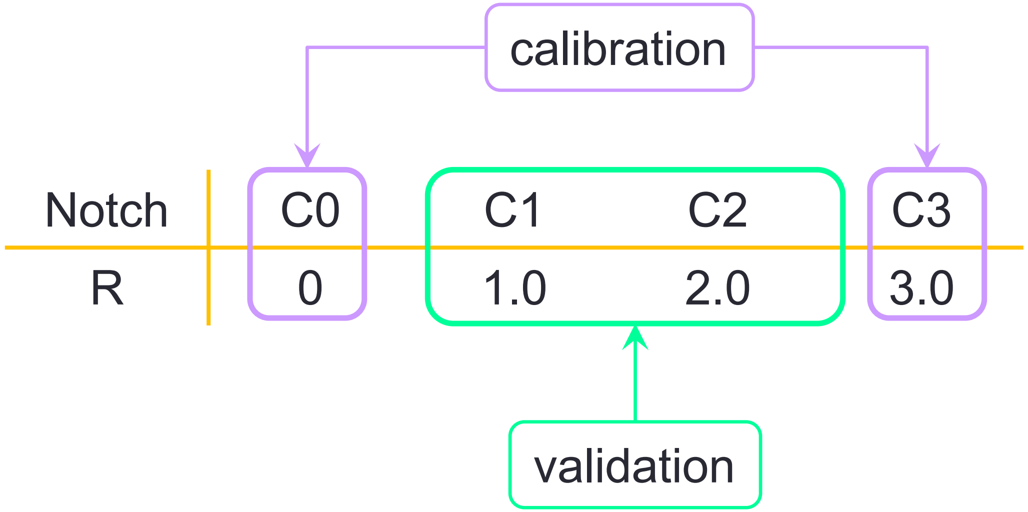


$$\eta_{avg} = \int \eta d\epsilon_{peeq}$$

Stage 3: Prediction of fracture using TS-ANN model – A572

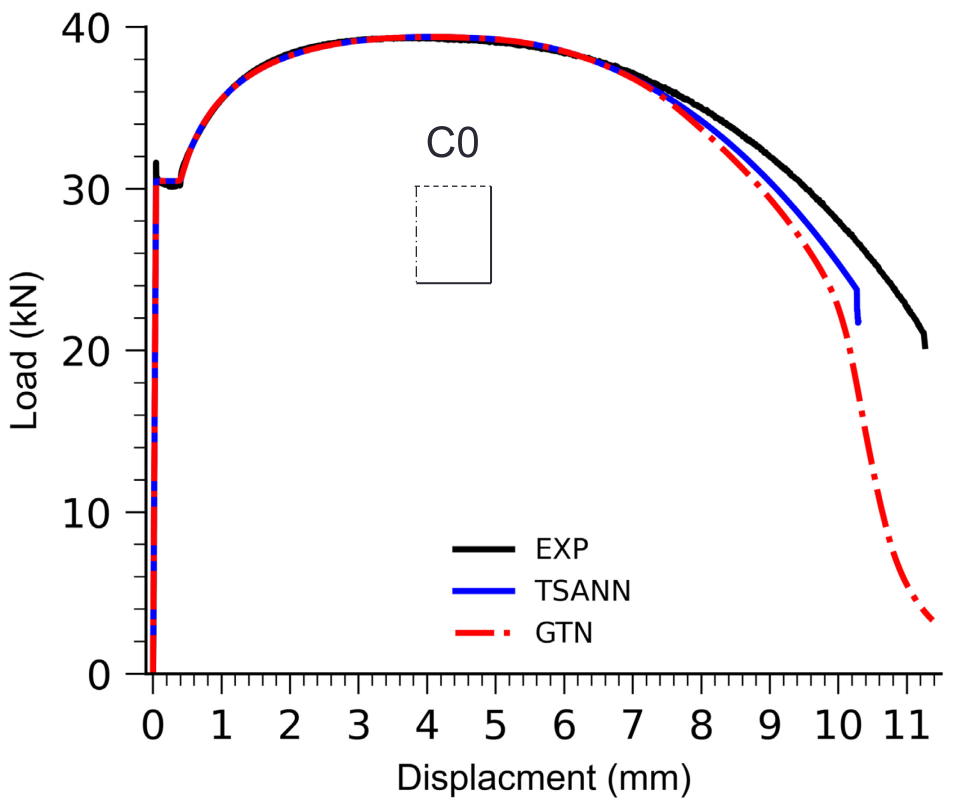


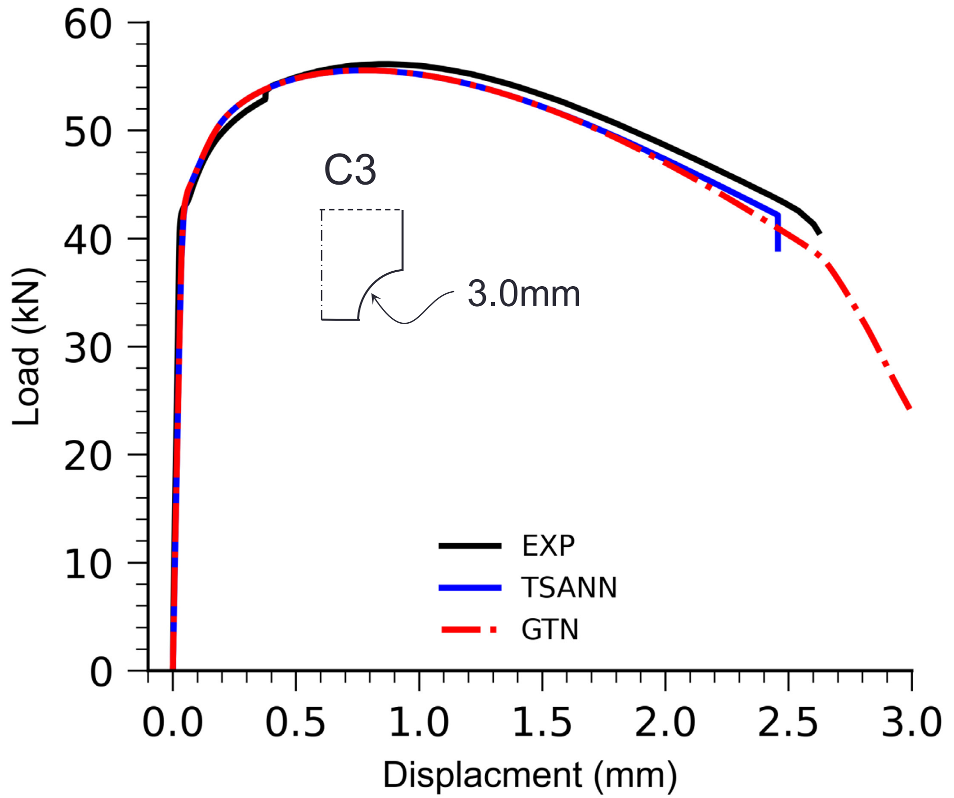
- A572 –notched tensile specimens
- One unnotched and three notched specimens used
- Involves various range of triaxiality - stress triaxiality at critical section varies 0.33 to 1.6



Source : Sajid, H. U., & Kiran, R. (2018). Influence of high stress triaxiality on mechanical strength of ASTM A36, ASTM A572 and ASTM A992 steels. Construction and Building Materials, 176, 129-134.

Stage 3: Calibration of TS-ANN model – A572

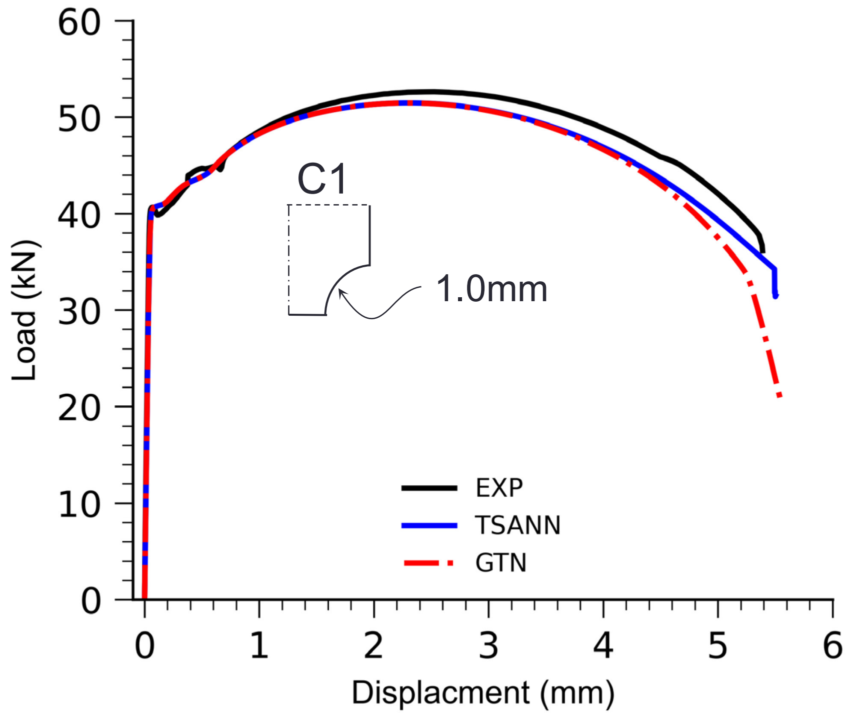


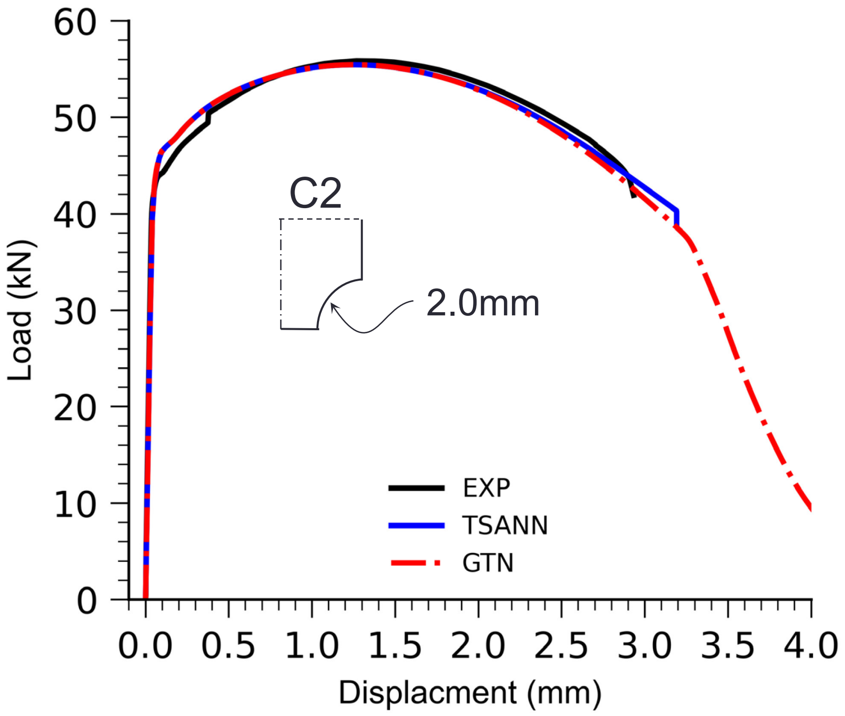


Specimen	Failure deformation u_f (mm)		Relative error (%)
	Experiment	TS-ANN	
C0	11.26	10.29	-8.6
C3	2.62	2.82	-6.1

TS-ANN Parameters	f_o	f_N	f_F	ε_N	s_N
Calibrated value	0.0015	0.0019	0.042	0.50	0.05

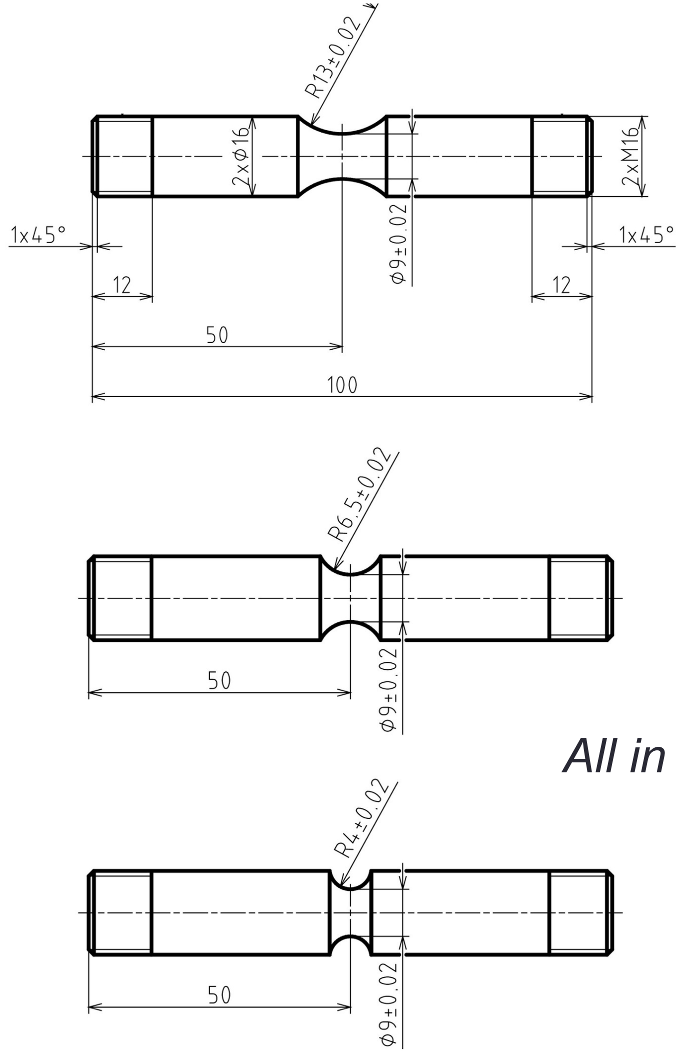
Stage 3: Prediction of fracture using TS-ANN model – A572





Specimen	Failure deformation u_f (mm)			Error (%)	
	Experiment	GTN	TS-ANN	GTN	TS-ANN
C1	5.39	5.25	5.5	-2.6	**2.0**
C2	2.93	3.26	3.19	11.3	**8.9**

Stage 3: Prediction of fracture using TS-ANN model – Aluminum



All in mm.

- Aluminum alloy 2024-T351 – Circular arc notched tensile specimens
- One unnotched with 6mm dia. and three notched specimens with 9mm core dia. And 16mm outer dia. used
- Involves various range of triaxiality - stress triaxiality at critical section varies 0.33 to 1.4

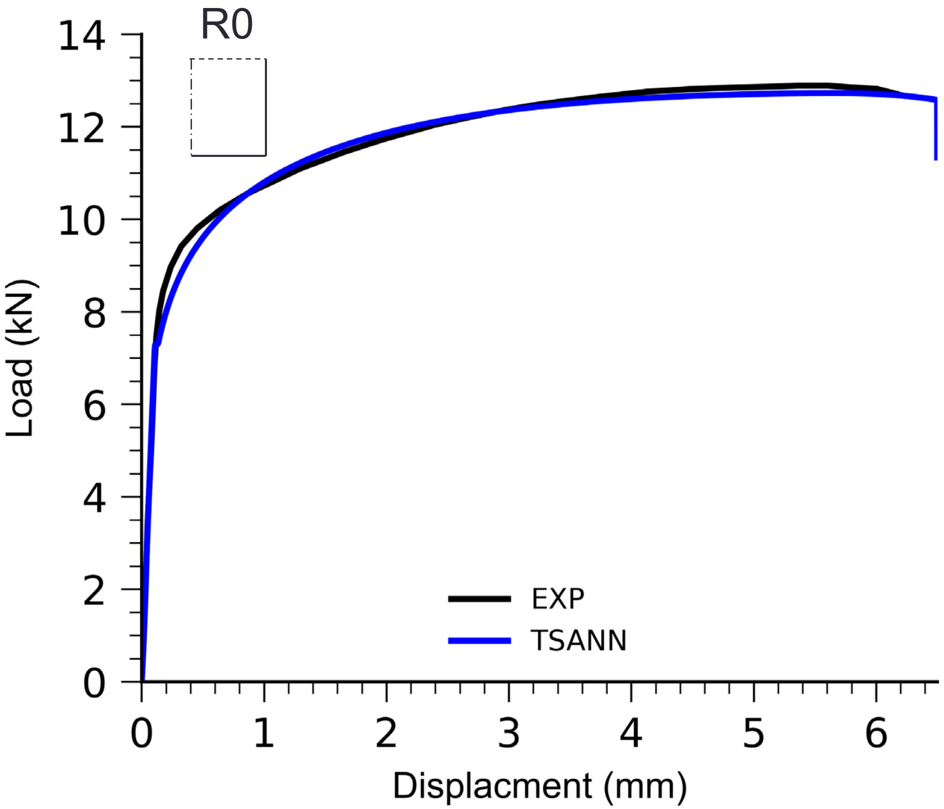
calibration

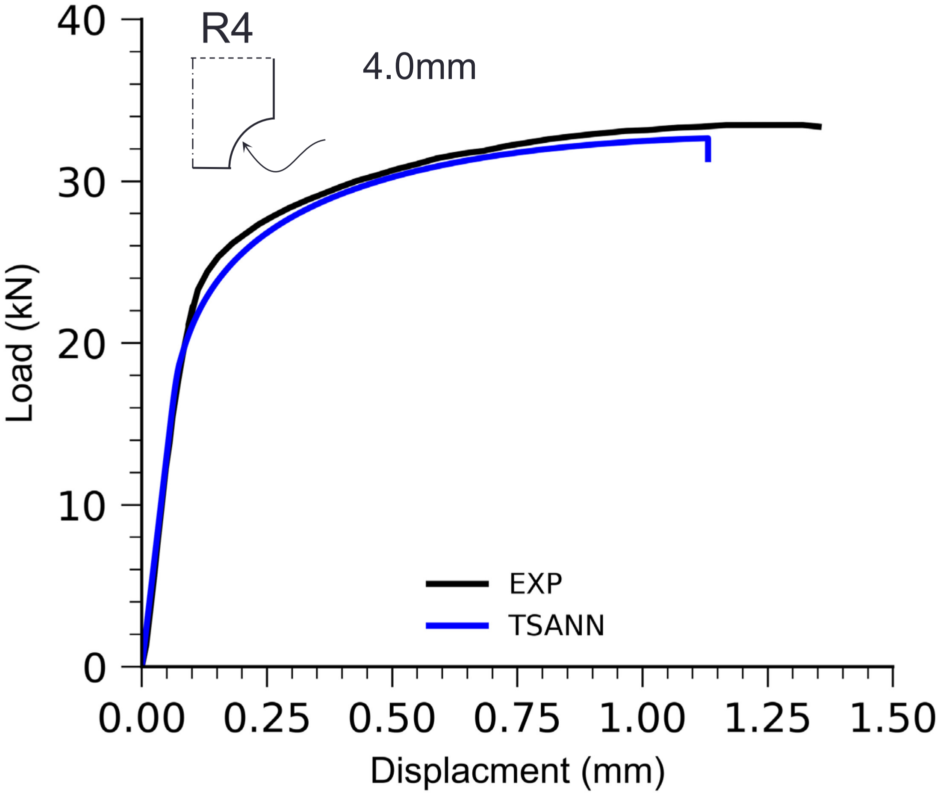
Notch	R0	R4	R6.5	R13
R	0	4	6.5	13

validation

Source : Šebek, F., Petruška, J., & Kubík, P. (2018). Lode dependent plasticity coupled with nonlinear damage accumulation for ductile fracture of aluminium alloy. Materials & Design, 137, 90-107.

Stage 3: Calibration of TS-ANN model – Aluminum

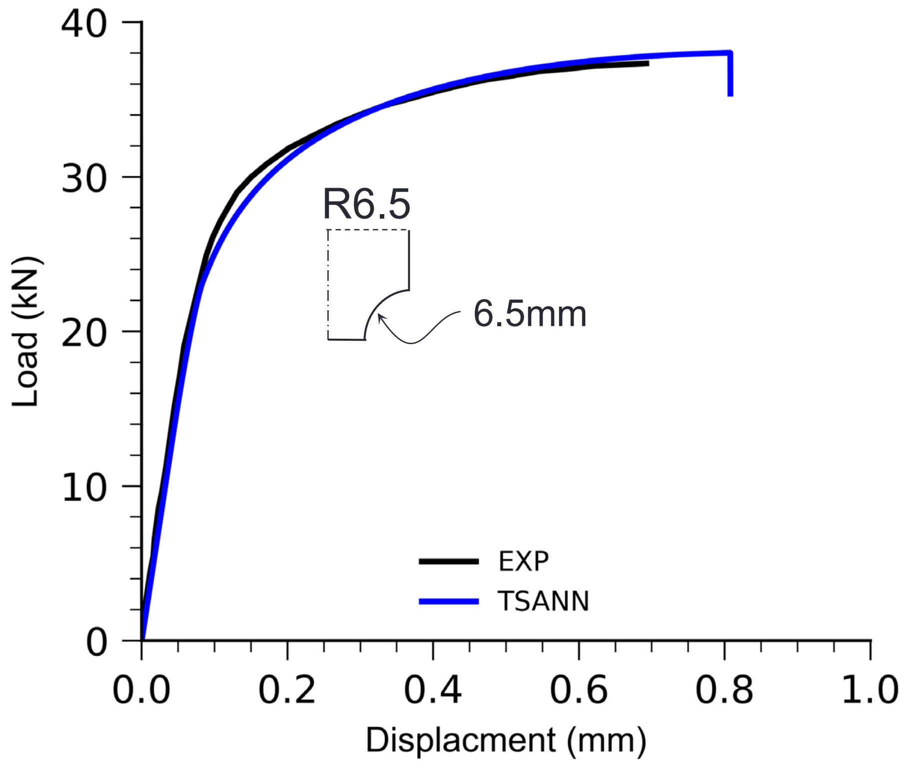


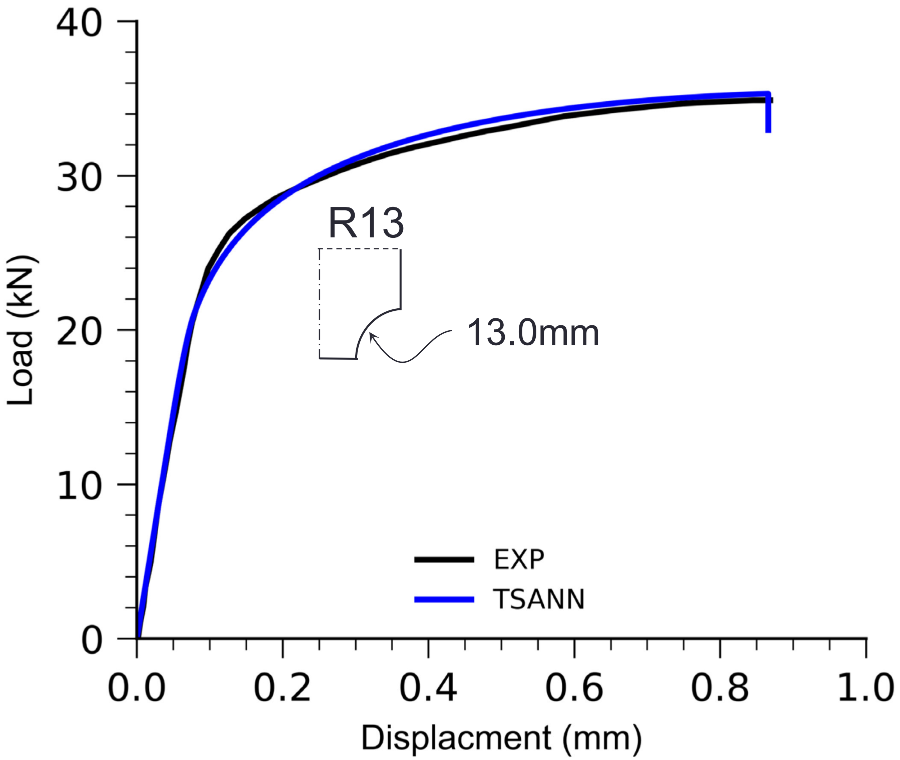


Specimen	Failure deformation u_f (mm)	
	Experiment	TS-ANN
R0	6.22	6.5
R13	1.35	1.13

TS ANN parameters	f_o	f_N	f_F	ε_N	s_N
Calibrated value	0.0085	0.009	0.023	0.10	0.05

Stage 3: Prediction of fracture using TS-ANN model – Aluminum





Specimen	Failure deformation u_f (mm)		Error
	Experiment	TS-ANN	TS-ANN
R6.5	0.69	0.81	**16.7**
R13	0.87	3.19	**0.3**

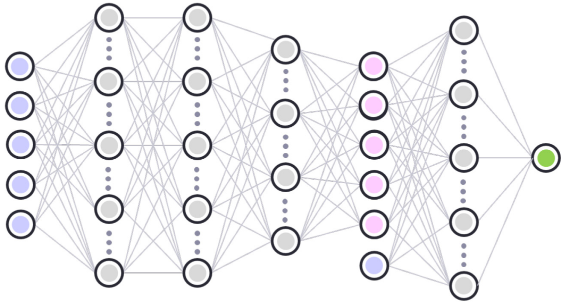
TS-ANN Model – Computational Performance

A572	Elements	Nodes	Mean Runtime (s) GTN	Mean Runtime (s) TS-ANN	Speedup factor
C0	2200	2295	640	41	15.6
C1	2976	3092	380	64	6
C2	3676	3809	320	32	10
C3	4236	4385	292	41	7.1

T351	Elements	Nodes	Mean Runtime (s) GTN	Mean Runtime (s) TS-ANN	Speedup factor
R0	1710	1798	340	34	10
R4	2898	3008	132	39	3.3
R6.5	2852	2961	132	40	3.3
R13	2745	2852	160	34	4.7

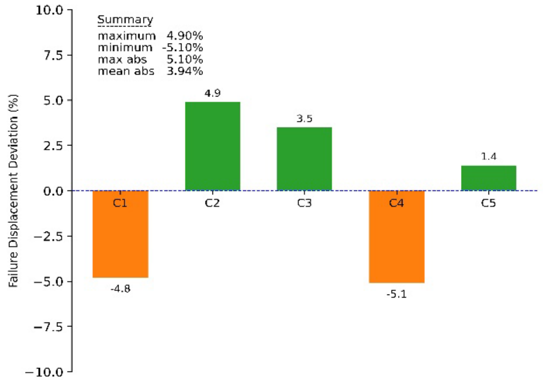
3-16 times faster than coupled GTN model

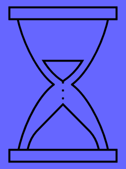
Important Takeaways



- Material agnostic data-driven model
- Extend to other fracture models
- Calibration of model parameters is easy

- Incorporates the high-fidelity of a coupled micromechanical model
- Fracture initiation predictions are **within 17%**





- Fracture analysis runtime ranged from 30-60s for 2000-4000 elements
- 3-16 times faster than coupled GTN analysis
- Can be scaled for large structures

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Thank you for your attention ☺