

# Advancing Blast Fragmentation Simulation of RC Slabs: A Graph Neural Network Approach

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# Introduction

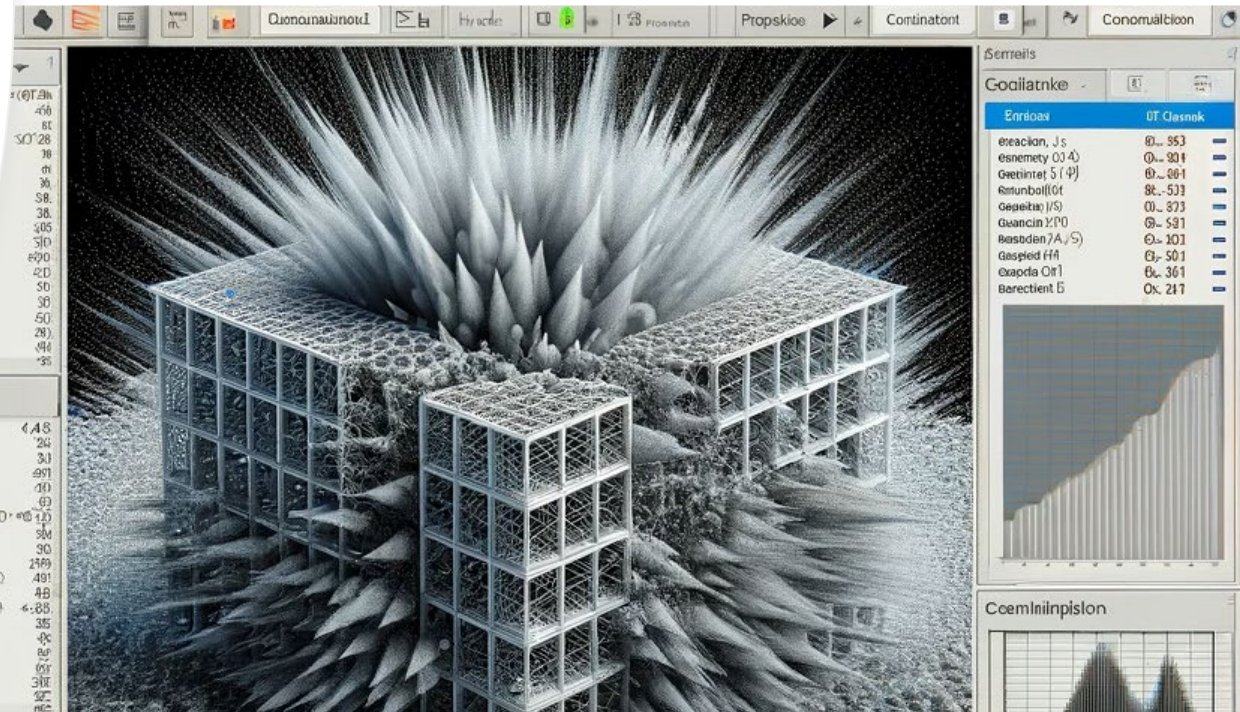
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- Blast fragmentation simulation is crucial
  - Predict and mitigate blast effects
  - Terrorist attacks or industrial accidents
- Accurate simulation aid protective design
  - Withstand blast impacts
  - Structural integrity and public safety



# Existing Approaches

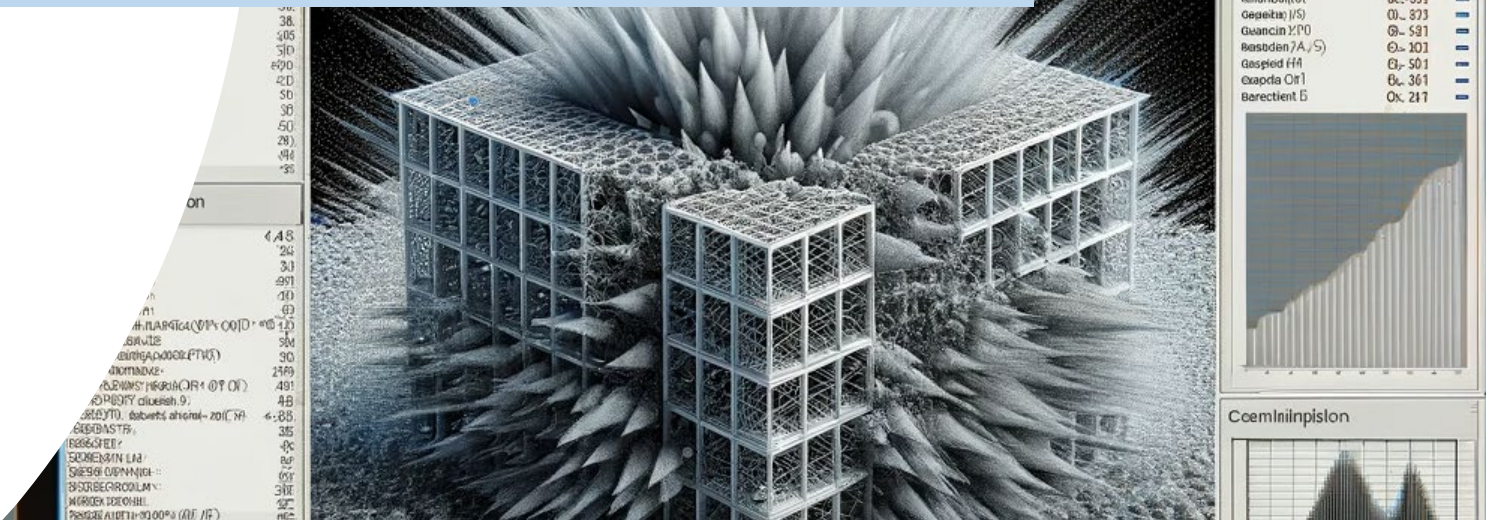
- Experimental testing
  - Expensive
  - Difficult to collect comprehensive data
- Numerical Modelling
  - Computationally intensive
  - Scalability



# Existing Approaches

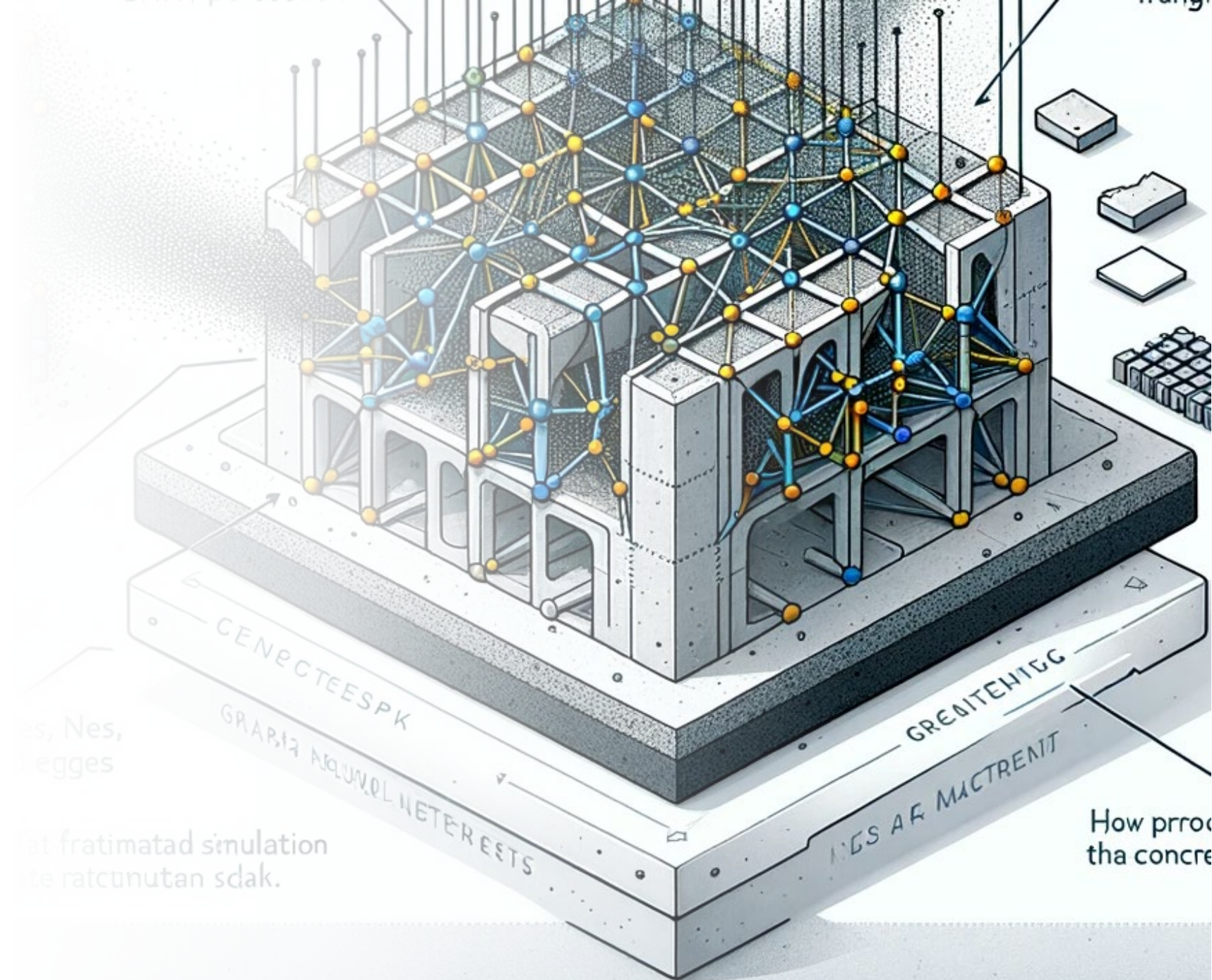
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We need a solution that reduce computational load without compromising accuracy!



# Overview of Graph Neural Networks (GNN)

- Brief explanation of GNN
  - Graph structured data + deep learning
  - Capturing interactions between elements
- Why GNN for this problem?
  - GNN is like FEM
  - Divide and conquer



# Numerical modelling

- FEM-SPH-ALE coupling

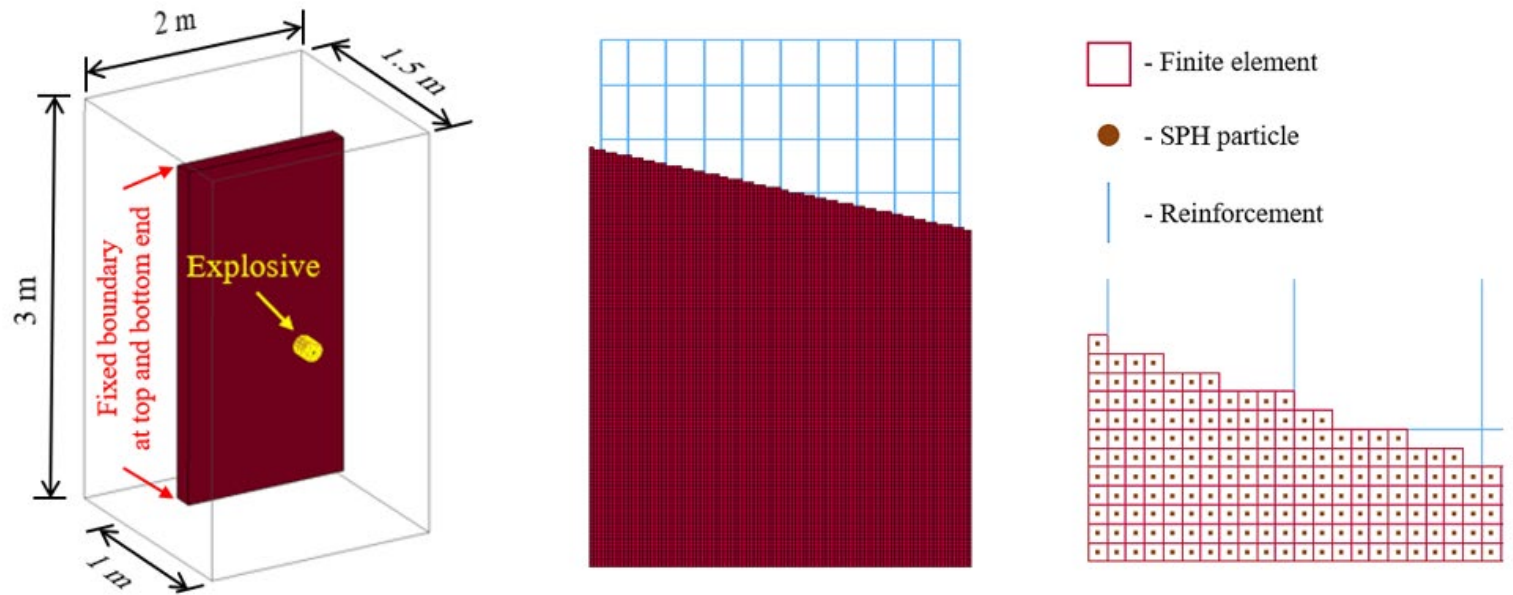


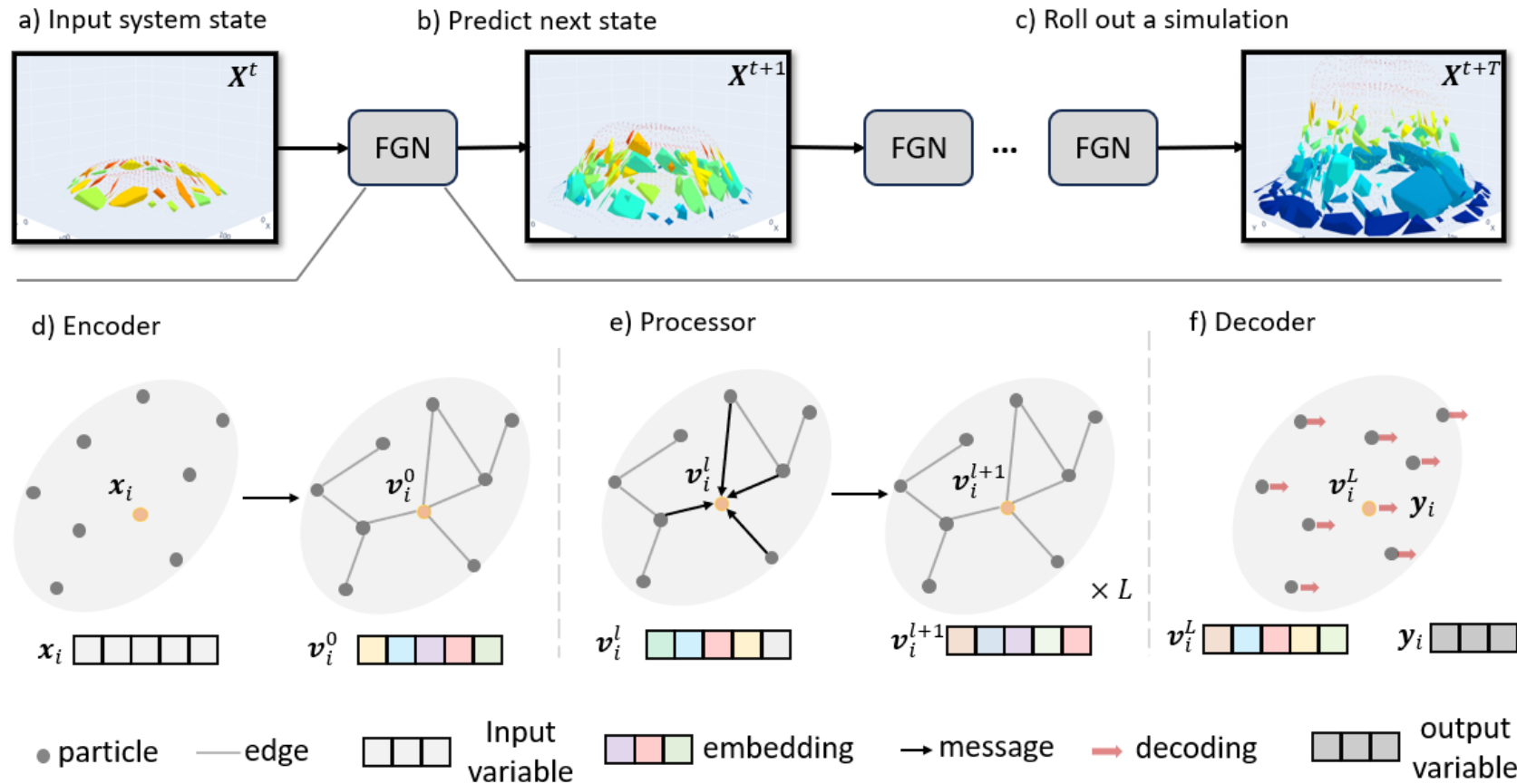
Table 3 Material properties of concrete [24, 53]

Density (kg/m <sup>3</sup> )	Poisson's ratio	Compressive strength (MPa)	Tensile strength (MPa)	A0	A1
2400	0.2	30.7	2.95	10.90125	0.466388
A2	A0Y	A1Y	A2Y	A1F	A2F
0.003641	6.923877	0.730823	0.005082	0.4773	0.003583

Table 4 Material properties of HRB 400 steel reinforcement [24]

Density (kg/m <sup>3</sup> )	Yield stress (MPa)	Ultimate stress (MPa)	Poisson's ratio	Young's modulus (MPa)
7,800	400	540	0.3	$2 \times 10^5$

# Fragment Graph Network (FGN)



# Training details

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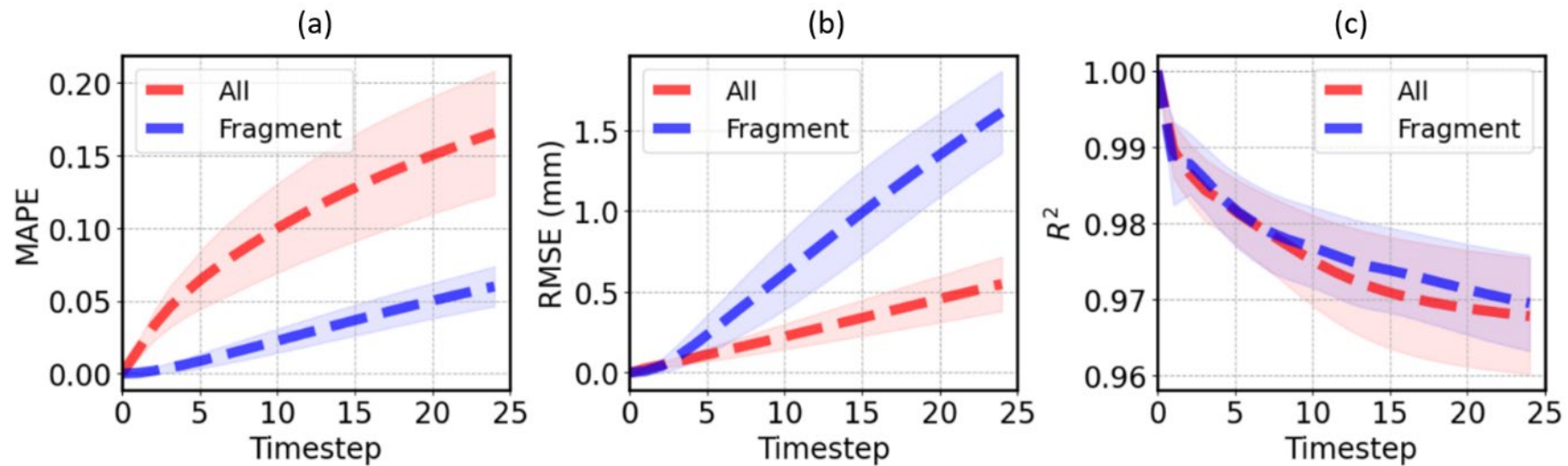
- 149 cases, each with ~180K particles for 35 steps over 2ms, 9M+ data points in total
- Trained on a NVIDIA TITAN RTX GPU for ~24h

Variable	Data range
Charge weight (kg)	2, 3, 4, 5, 6
Standoff distance (mm)	300, 400, 500
Concrete strength	C30, C50, C80
Slab size (mm) and reinforcement layout	1000×2000×60, H $\varphi$ 12@100, V $\varphi$ 12@200 (one layer) 1000×2000×90, H $\varphi$ 12@100, V $\varphi$ 12@200 (two layers) 1000×2000×120, H $\varphi$ 12@100, V $\varphi$ 12@200 (two layers with stirrup)



# Overall Quantitative Evaluation

- Averaged over all particles or fragment particles
- Fragments: ~6% relative error, 1.7 mm absolute error, 96%+  $R^2$



# Time and Memory Efficiency

- FGN is several magnitudes faster than LS-DYNA
- And consumes less memory, which makes it more scalable

Table 6 Runtime comparison between LS-DYNA and FGN

Number of particles	Runtime (second)		
	LS-DYNA-CPU	FGN-CPU	FGN-GPU
123K	10,560	74	5
186K	10,800	116	8
246K	11,400	146	12

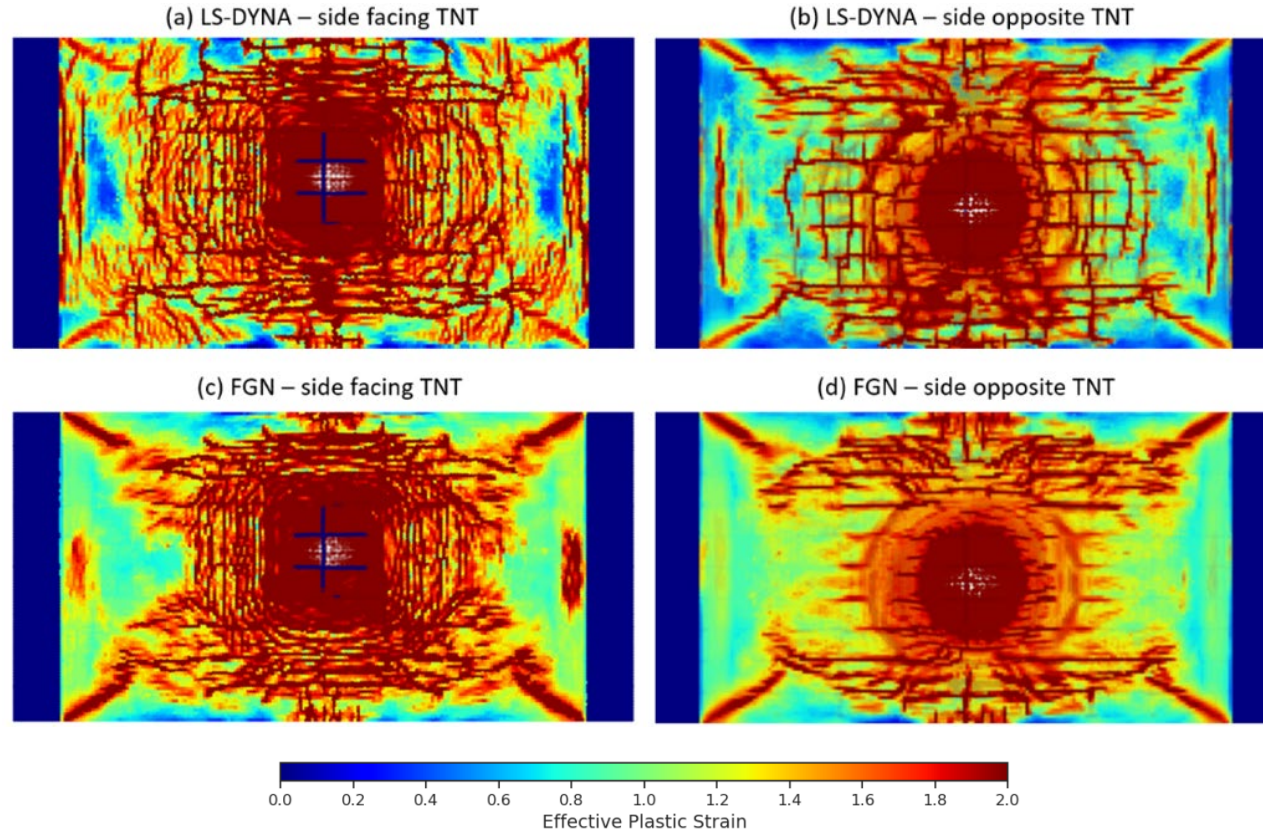
Table 7 Maximum memory usage comparison between LS-DYNA and FGN

Phase	Memory Usage (GB)		
	LS-DYNA-CPU	FGN-CPU	FGN-GPU
Training	-	23	24
Inference	62	16	21

# Effective Plastic Strain Prediction

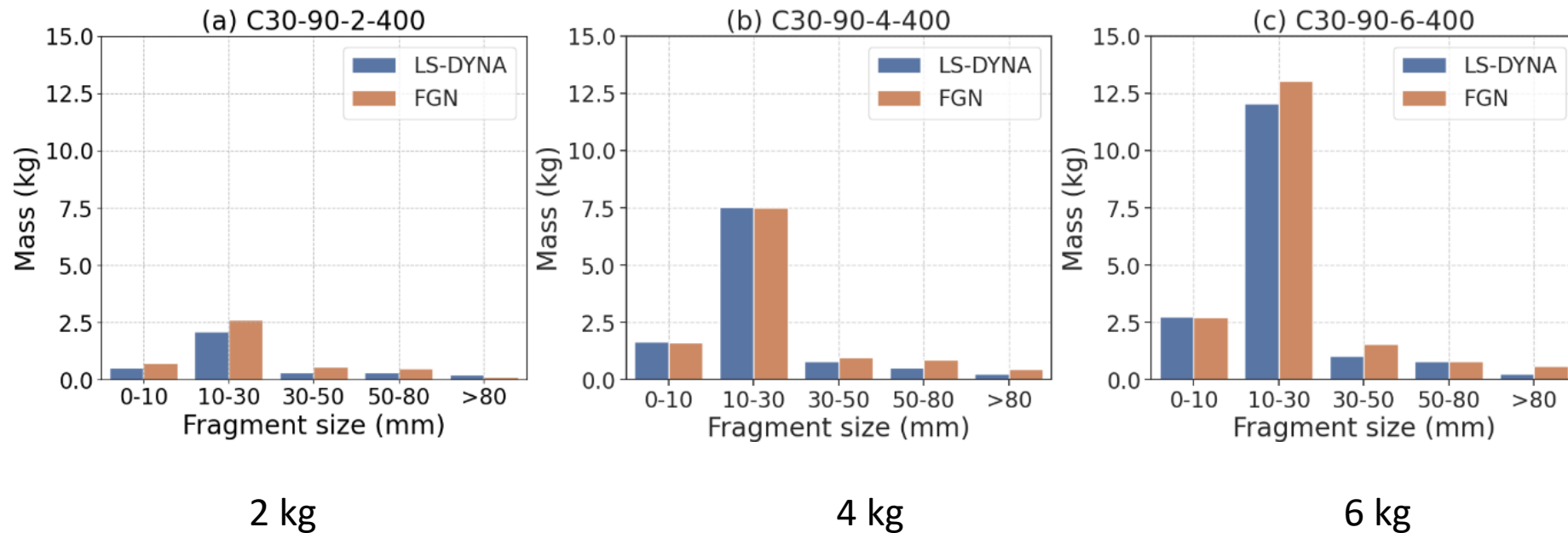
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- FGN can predict other parameters, e.g., effective plastic strain



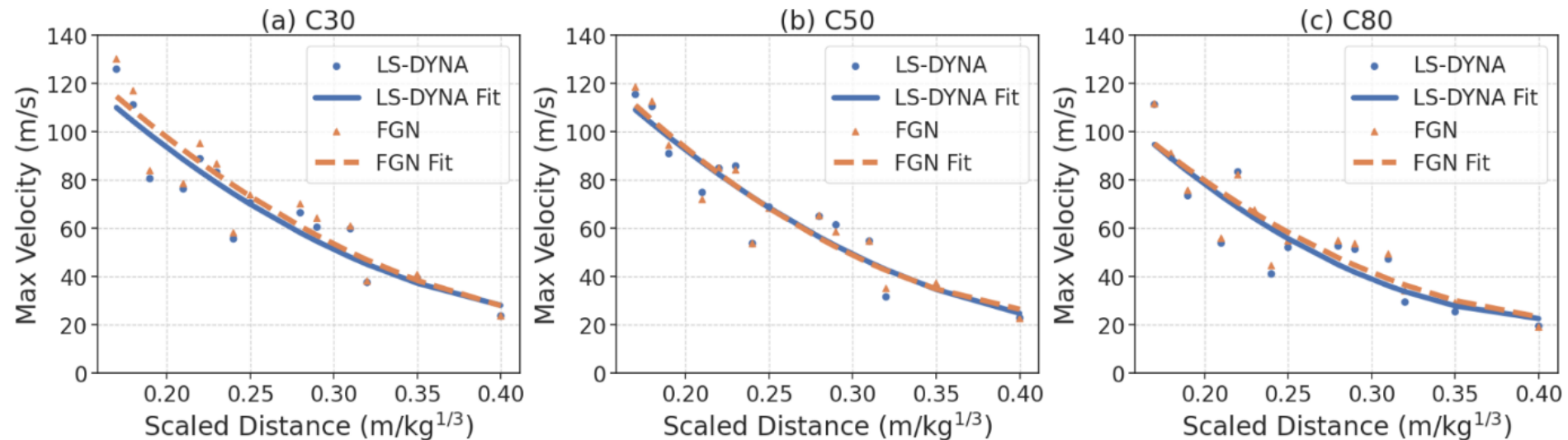
# Fragments Mass Distribution

- FGN matches well with LS-DYNA, in terms of fragments distribution



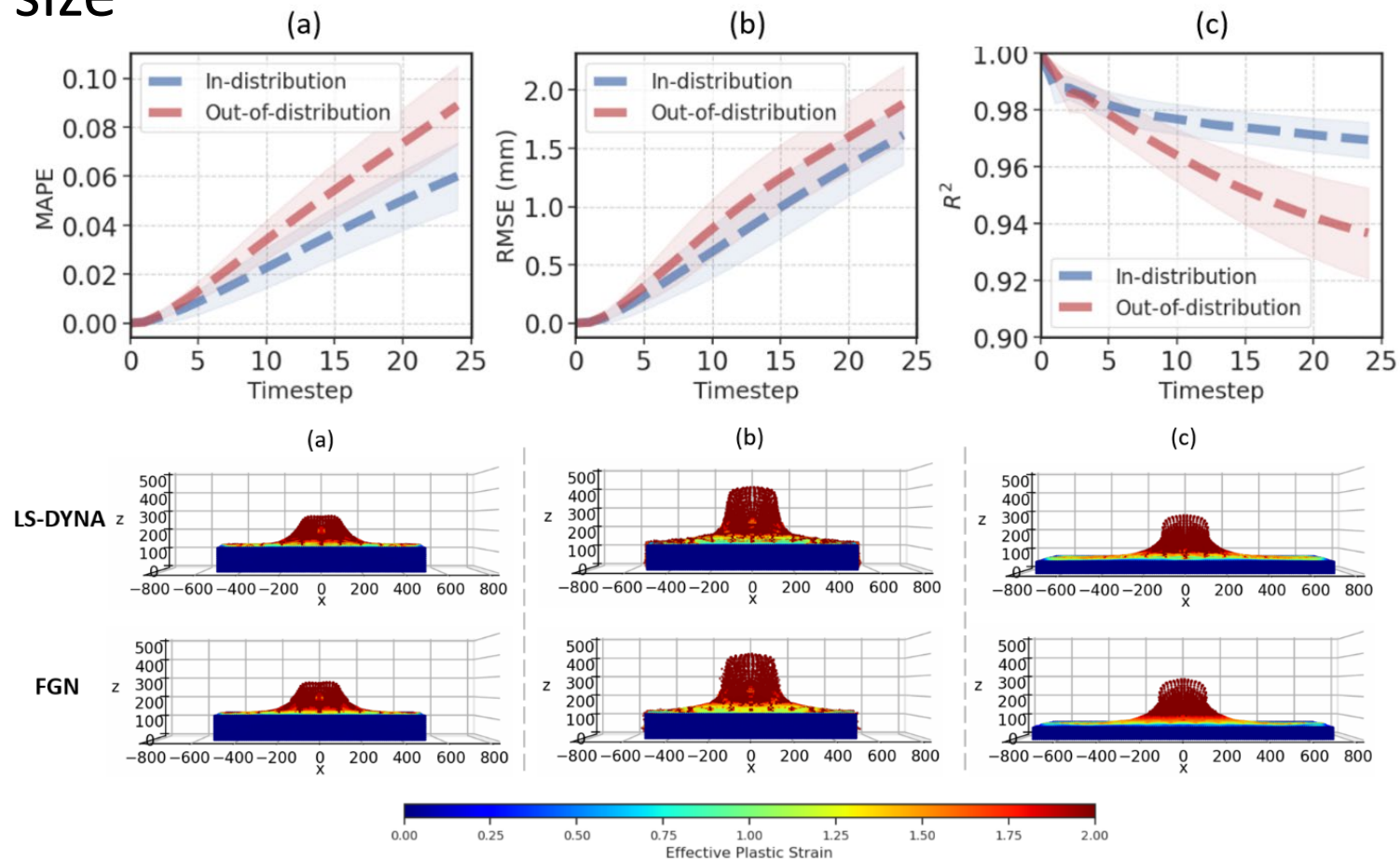
# Fragments Max Ejection Speed

- FGN well capture the max ejection speed of fragments
- FGN is well suited for data-hungry parametric analysis



# Generalization and Robustness

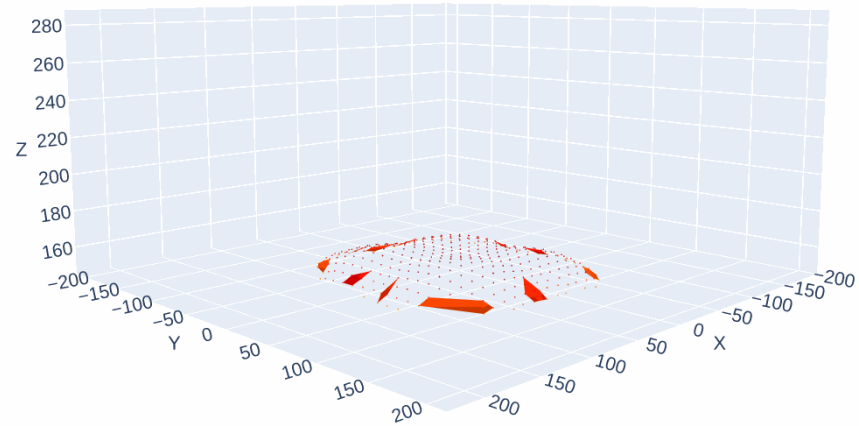
- FGN exhibits good generalizability, e.g., extrapolating scaled distance or slab size



# Simulation Animation

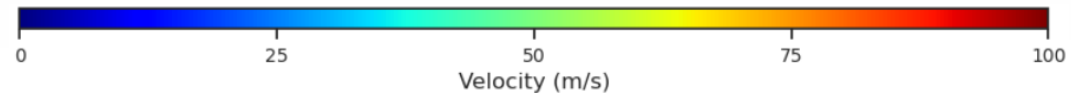
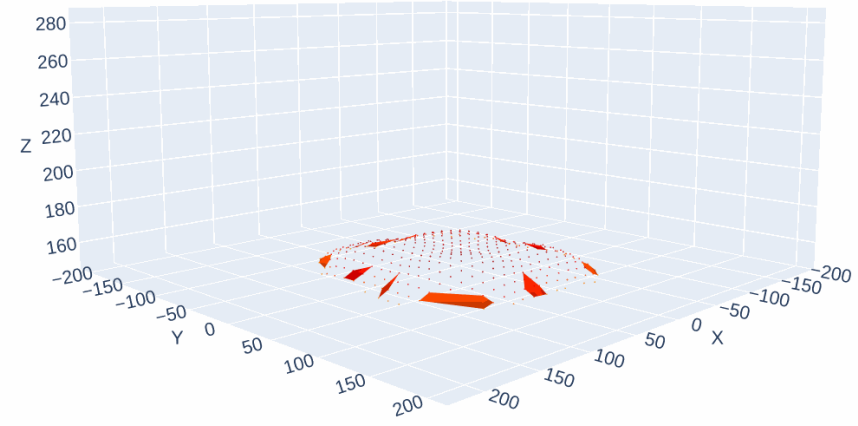
LS-DYNA

Step: 00, time: 0.600 ms, fragment mass: 0.840 kg



FGN

Step: 00, time: 0.600 ms, fragment mass: 0.840 kg



# Takeaway

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- GNN is well suited for surrogating discretization-based numerical modelling, such as FEM, SPH, or even Eulerian grid
- Paper and code
  - Li, Qilin, Yang Wang, Wensu Chen, Ling Li, and Hong Hao.  
"Machine learning prediction of BLEVE loading with graph neural networks."  
*Reliability Engineering & System Safety* 241 (2024): 109639.  
<https://github.com/qilinli/bleve-graph-net>
  - Li, Qilin, Zitong Wang, Ling Li, Hong Hao, Wensu Chen, and Yanda Shao.  
"Machine learning prediction of structural dynamic responses using graph neural networks."  
*Computers & Structures* 289 (2023): 107188.  
<https://github.com/qilinli/gns-fragment>



Thank you for your  
attention!  
Questions?

