Advanced Analysis and Optimization of Marine Structures

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Seaspan Vancouver Shipyard, August 20, 2024

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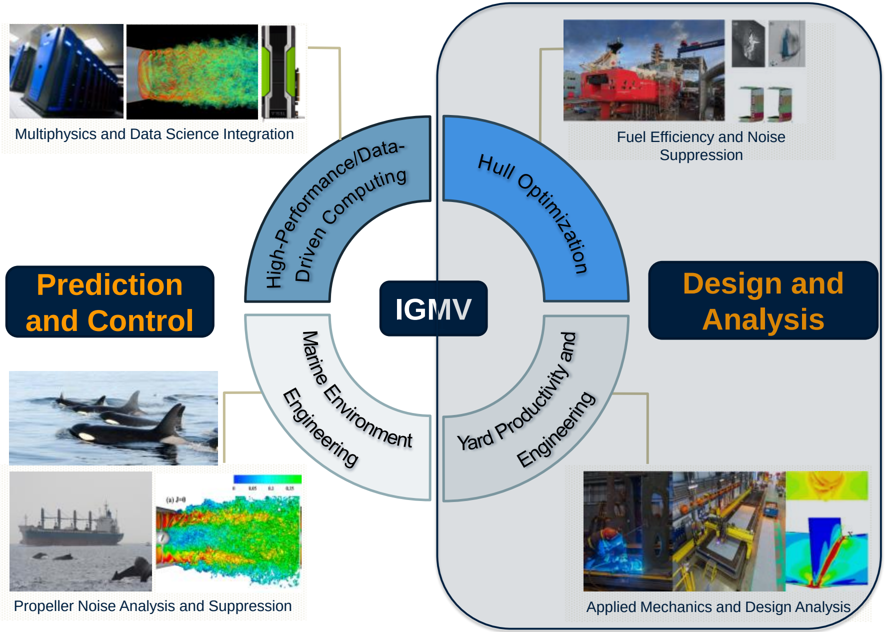

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Effects of small LNG spills on ship structures

Structural model:

$$u(r,z,t) = u_0(r,t) + z\varphi(r,t)$$
$$w(r,z,t) = w_0(r,t)$$

$$\varepsilon_{rr} = u_{,r} + \frac{1}{2}w_{,r}^2\ ;\ \varepsilon_{\theta\theta} = \frac{u}{r}\ ;\ \gamma_{rz} = u_{,z} + w_{,r}$$

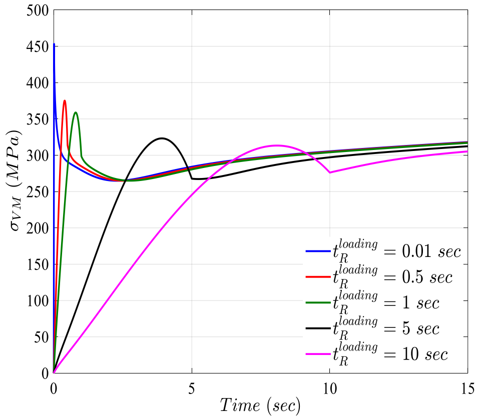
$$\begin{Bmatrix}\sigma_{rr}\\ \sigma_{\theta\theta}\\ \tau_{rz}\end{Bmatrix} = \begin{bmatrix}Q_{11} & Q_{12} & 0\\ Q_{12} & Q_{22} & 0\\ 0 & 0 & Q_{55}\end{bmatrix}\left(\begin{Bmatrix}\varepsilon_{rr}\\ \varepsilon_{\theta\theta}\\ \gamma_{rz}\end{Bmatrix} - \Delta T\begin{Bmatrix}\alpha\\ \alpha\\ 0\end{Bmatrix}\right)$$

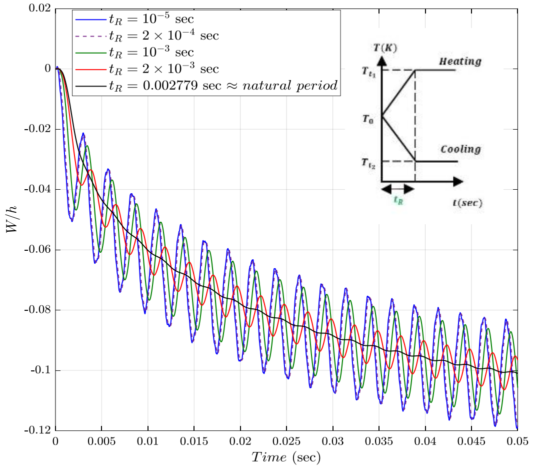
Eq. of motion solved via GDQ (time derivatives through Crank-Nicolson):

$$[M(T)]\{\ddot{\mathcal{X}}\} + [K(T,\mathcal{X})]\{\mathcal{X}\} = \{\mathcal{F}(T)\}$$

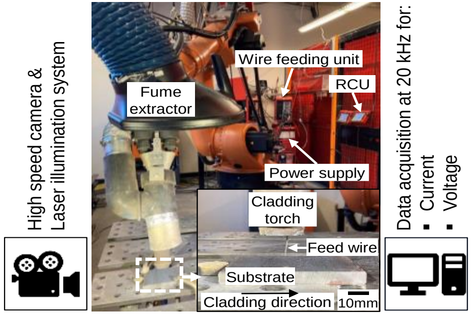
Heat equation

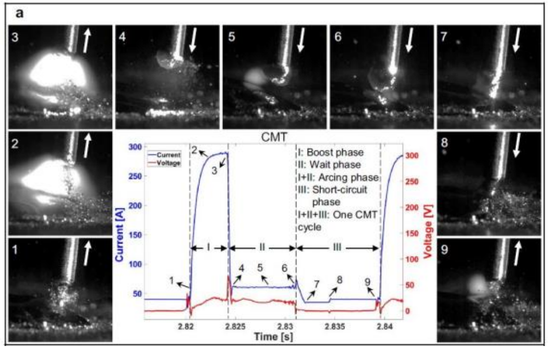
$$\left(\kappa(z,T)T_{,i}\right)_{,i} = \rho(z,T)C_v(z,T)\dot{T}$$

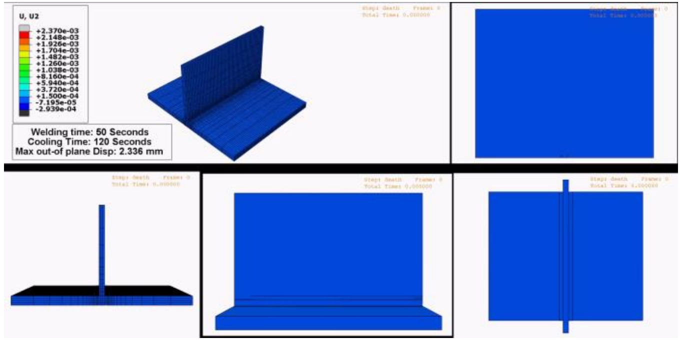


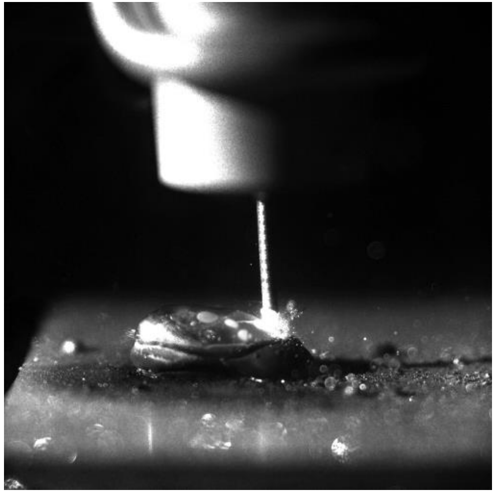


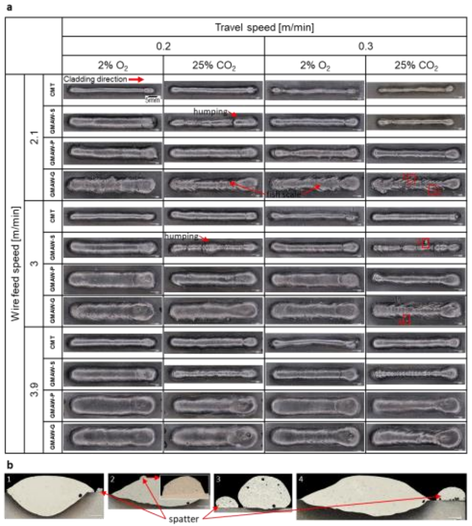
Welding experiments and simulations

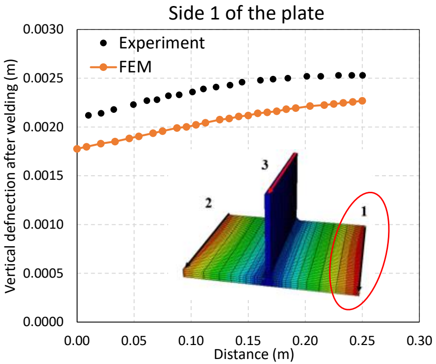










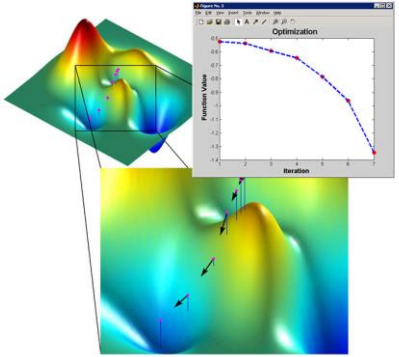


Karimi et al. *IJAMT*, 2023.

Structural optimization

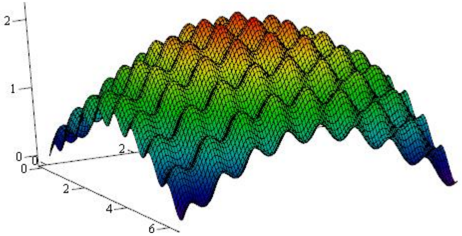
- Optimization of ship structures/production is a complex task with conflicting goals
- Commonly approached via manual iterations in the virtual space using structural simulation models → time consuming and potentially missing optimal designs
- If the structure (“system”) is modelled appropriately, computer optimization algorithms can be used to find the optimum
- Design landscape demands the use of iterative, global optimization algorithms

Sizing optimization via metaheuristic optimization algorithms



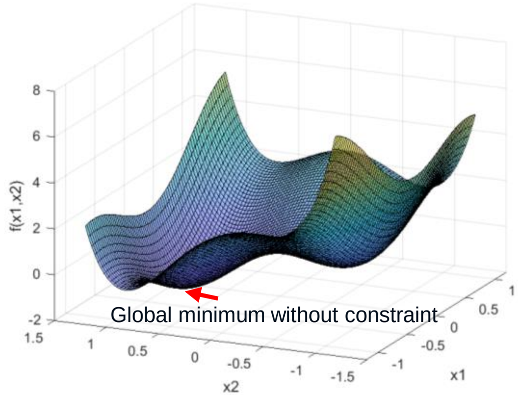
- Metaheuristics inspired by natural phenomena or biological behavior/mechanisms
- A set of designs (points) improved iteratively as a collective (knowledge shared in the process)

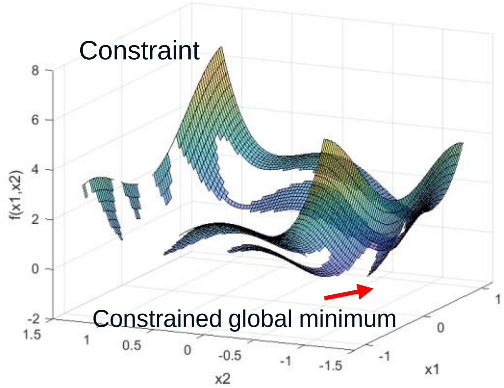
- **Advantages:** Robust and fairly accurate
- **Disadvantage:** Computationally inefficient
  - Gradient information replaced with large amount of data, i.e. many potential solutions
  - Large number of function evaluations necessary (10^3 - 10^5)
- **Remedies:**
  - Improve efficiency of optimization algorithms -> Goal 1
  - Use surrogate models of various types -> Goal 2



Constraints in optimization

- Constraints are restricting both design space and objective space
- In structural problems, constraints could be failure criteria or manufacturing requirements
- The global optimum might differ when constraints are introduced



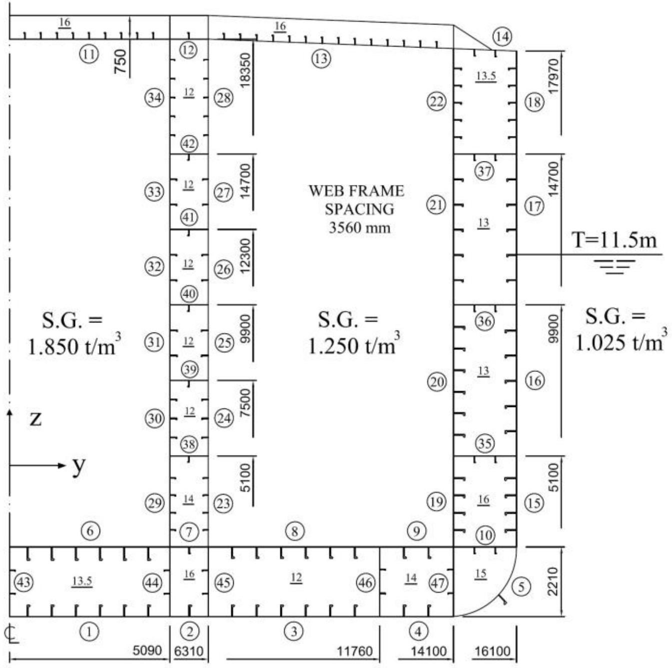


Hull girder test case

- L = 180 m, B = 32 m
- Midship section in focus

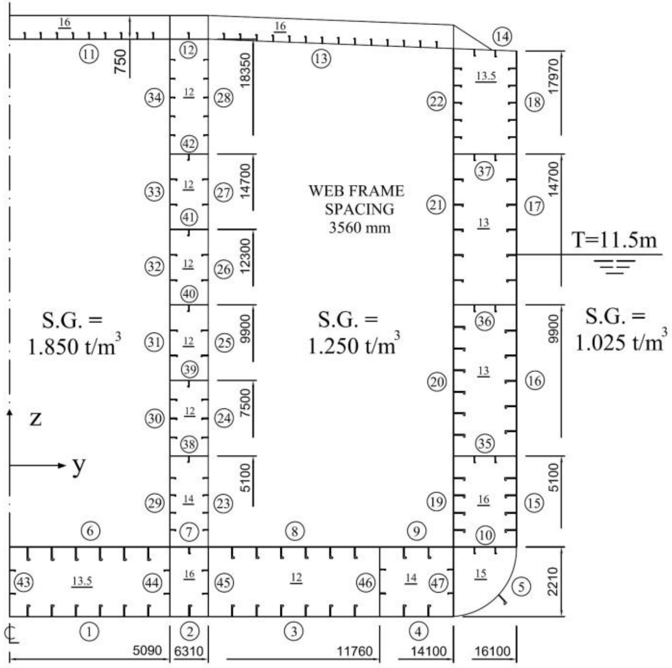
- Loading condition:
- Full cargo tanks, empty ballast tanks
- Hydrostatic sea pressure
- Considered under maximum bending moment and maximum shear force (L/4 and L/2)

- Global response using **coupled-beam method**
- Local response using Euler-Bernoulli beam theory, Kirchhoff plate theory
- DNV class rules and failure criteria



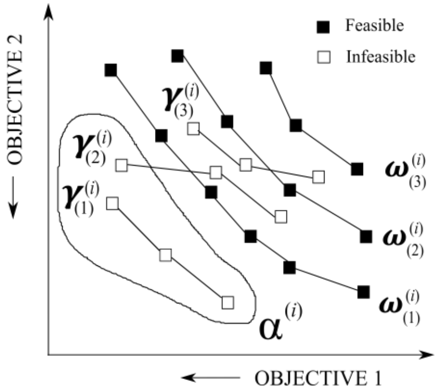
Hull girder test case

- Design variables:
  - Plate thicknesses and stiffener sizes
  - 47 strakes = 94 variables
- Constraints:
  - Plate yield and buckling
  - Stiffener yield, lateral and torsional buckling,
  - Stiffener's web and flange buckling
  - Crossover
  - 8 constraints per strake = 376 constraints
- Objectives:
  - Structural mass (prismatic ship)
  - Maximization of deck adequacy (Stress minimization in the deck)

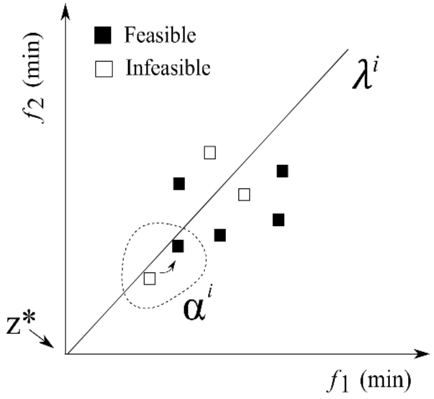


Adaptive repair technique

- **Adaptive repair constraint handling approach**:
  - High performance *infeasible* solutions are repaired based on other members of the population
  - Repair is performed by replacing variables that cause infeasibility
  - Based on <u>variable-constraint mapping</u>, constraint violations can be traced *back to variables*



Repairing in NSGA-II-R [1]



Repairing in MOEA/D-R [2]

[1] Samanipour and Jelovica, *Appl Soft Computing*, 2020
[2] Cai and Jelovica, *Engineering Optimization*, 2022

Neural network for discovery of the mapping matrix

- Determine the importance of each variable on each constraint by:
    - Set variables as inputs and constraints as outputs of the NN
    - Set the weight of an input neuron (variable) to zero and observe the change in an output neuron (constraint)
    - Variable with highest influence is determined, removed, and process is repeated to find other important variables with influence above a threshold

$$
\begin{array}{cc}
 & \text{variables} \\
\text{constraints} & \begin{bmatrix}
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\end{bmatrix}
\end{array}
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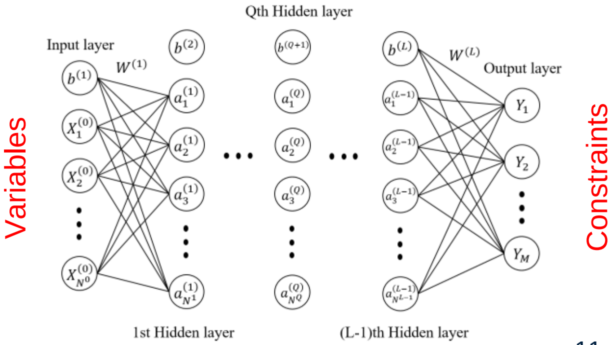
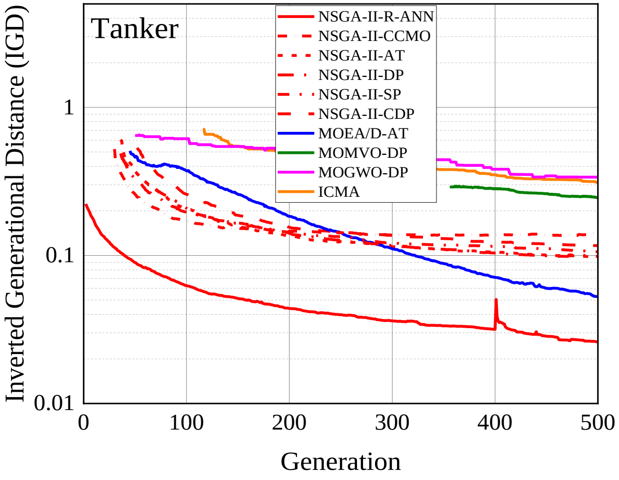
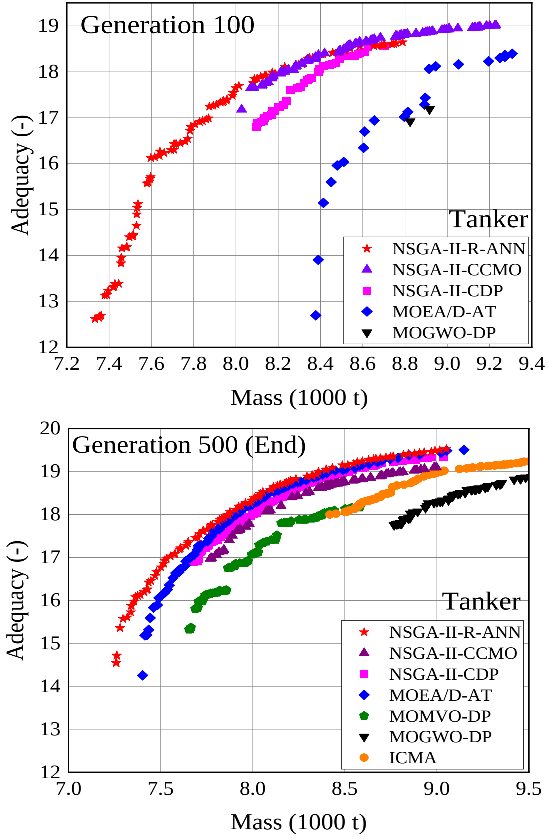


Cai and Jelovica, *Knowledge-Based Systems*, 2023

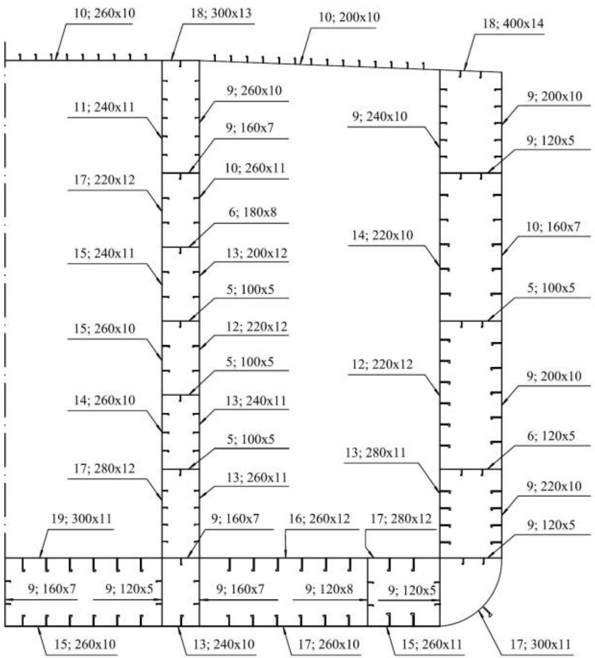
Results



Median values based on 30 runs for each algorithm/CHT

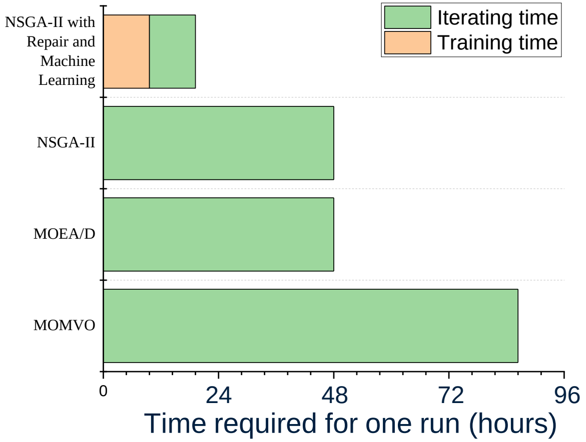


Pareto front at intermediate and final optimization step



Minimum mass design

Computational requirements



Benchmark algorithm with our modifications

Benchmark algorithm

Improved benchmark algorithm

State-of-art algorithm

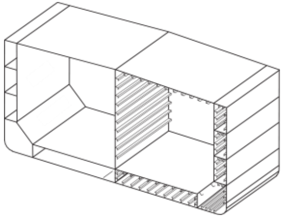
- Each hull girder analysis took 3 seconds; to achieve this, prismatic ship was assumed, which is inappropriate for detailed design or production support stages
- Accurate and fast surrogate models are needed for analysis of complicated geometries, trained on FEA, that are generalizable and scalable

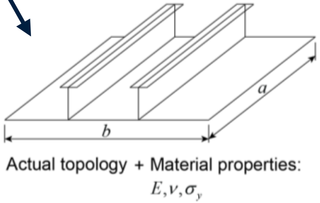
Homogenization and Equivalent Single-Layer (ESL)

Pre-processing:

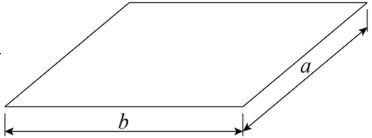
- Less details to model, fewer nodes and elements

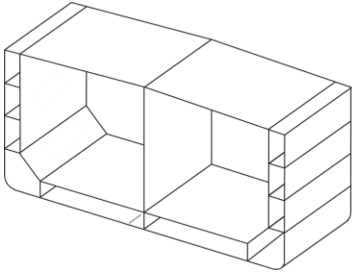
3D Stiffened plate



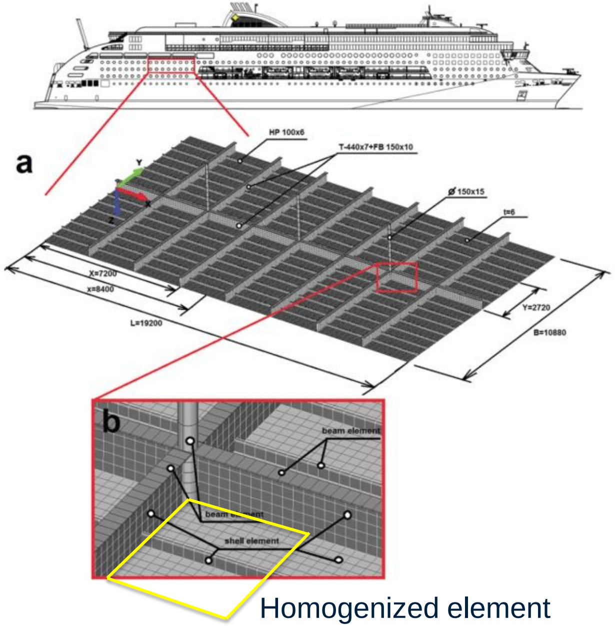


Equivalent 2D ESL plate



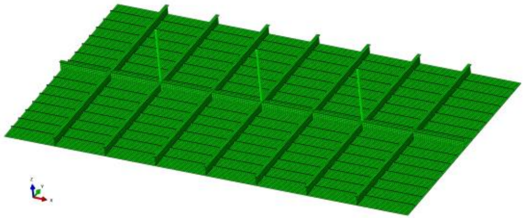


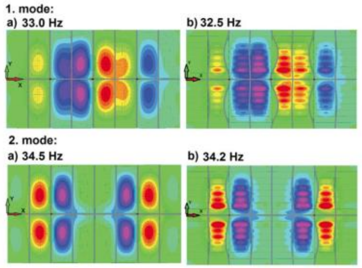
- Computationally efficient simulations

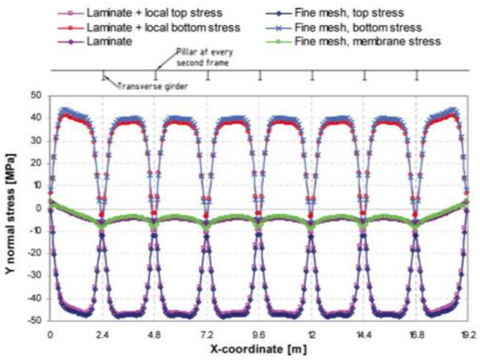


Homogenized element

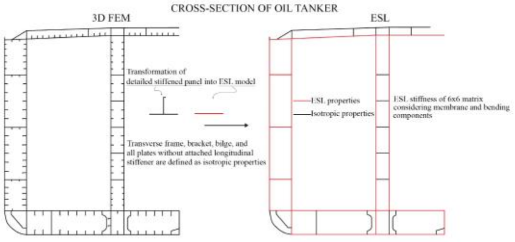
Examples of ESL simulations



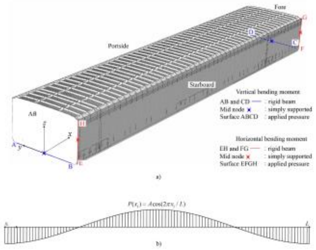




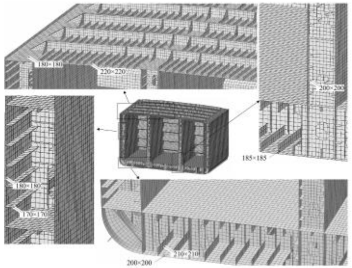
Avi et al. *SAOS*, 2015



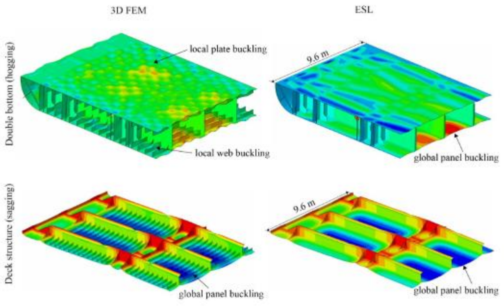
Modeling approach



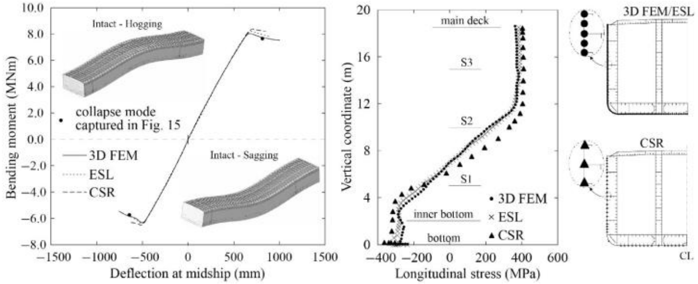
Entire 3D model



3D mesh



Collapse mode in double bottom and main deck structures



Moment-deflection curves and post-collapse longitudinal stress distribution

98% reduction of analysis time

Putranto et al. *JMSE*, 2023

Introduction to graphs

- A graph can be represented as: $g = (v_g, \varepsilon_g, \chi_g, E_g)$

  v_g : A set of vertexes

  ε_g : A set of edges

  χ_g : Domain of vertexes

  E_g : Domain of edges

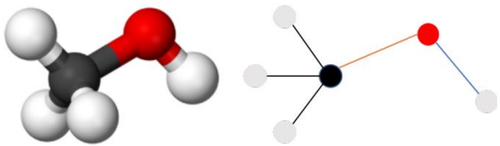


Image from internet

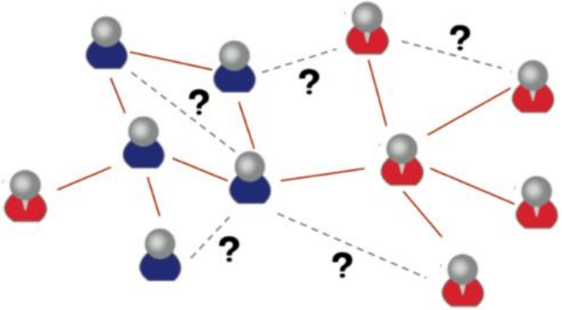


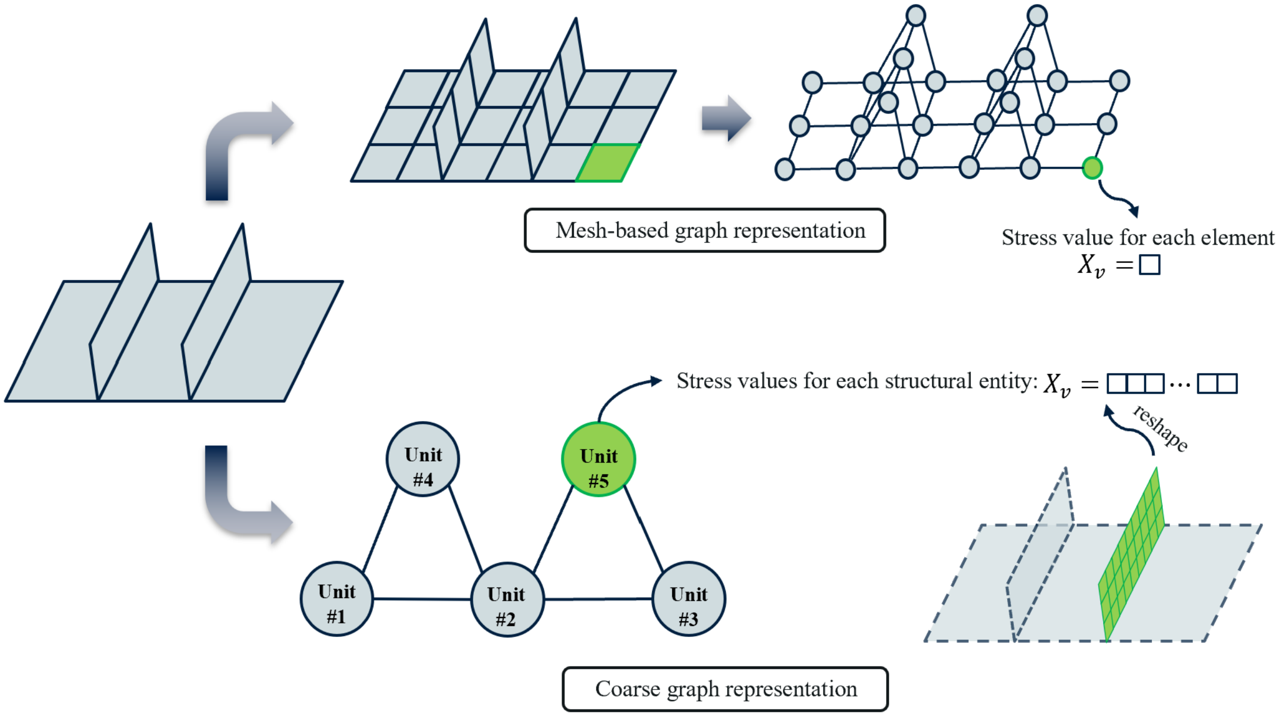
Image from internet

- Graph Neural Network (GNN)

  1. Capable of handling graphs with different structures (mechanical structures with different geometries)
  2. Ability to capture complex relationships;
  3. Interpretable and explainable representations

Graph representation of stiffened panel

- Proposed graph embedding for stiffened panels



Cai and Jelovica, *TWS*, 2024

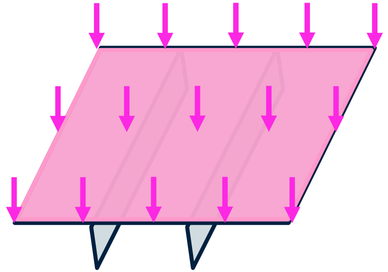
Dataset preparation

- **Stiffened panel dimension:**
  - ➢ Width: 3m
  - ➢ Height: 3m

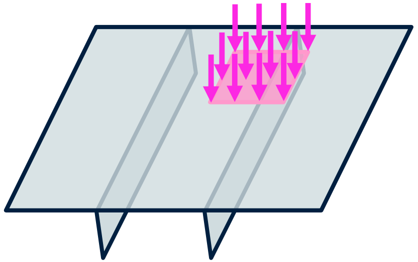
- **Parameter space:**

Category	Lower limit	Upper limit	Unit
Plate thickness	10	20	mm
Stiffener web thickness	5	20	mm
Stiffener web height	100	400	mm
Flange thickness	5	20	mm
Flange width	50	150	mm
Number of longitudinal stiffeners	2	8	-
Number of transverse stiffeners	0	3	-
Plate curvature for curved panels	0	0.015	1/m^2

- **Uniform loading (0.05~0.2 MPa)**



- **Patch loading (0.05~0.2 MPa)**



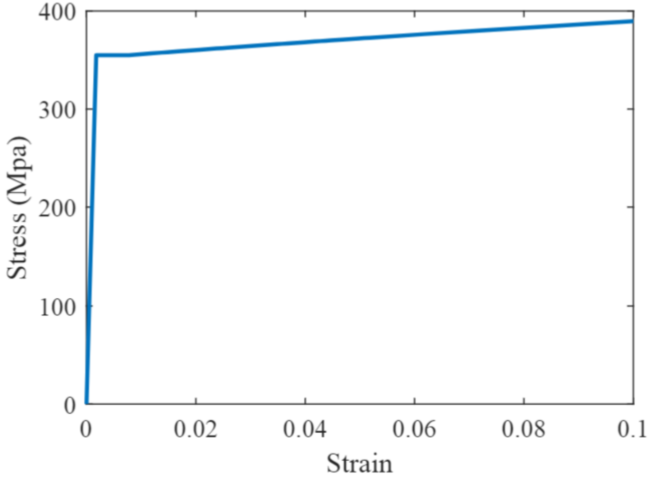
Dataset preparation

- **Material nonlinearity**

$$\sigma_f(\bar{\varepsilon}) = \begin{cases} \sigma_0 & if\ \ \bar{\varepsilon} \le \varepsilon_L \\ K(\bar{\varepsilon}_0 + \bar{\varepsilon})^n & if\ \ \bar{\varepsilon} > \varepsilon_L \end{cases}$$

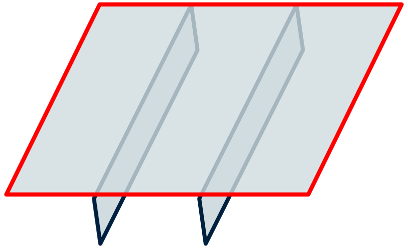
$$\bar{\varepsilon}_0 = (\sigma_0/K)^{1/n} - \varepsilon_L$$

  - Plateau strain ε_L = 0.006; work hardening parameters *K* = 530 Mpa, and *n* = 0.26

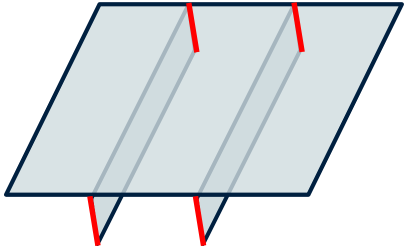


- **Boundary conditions**

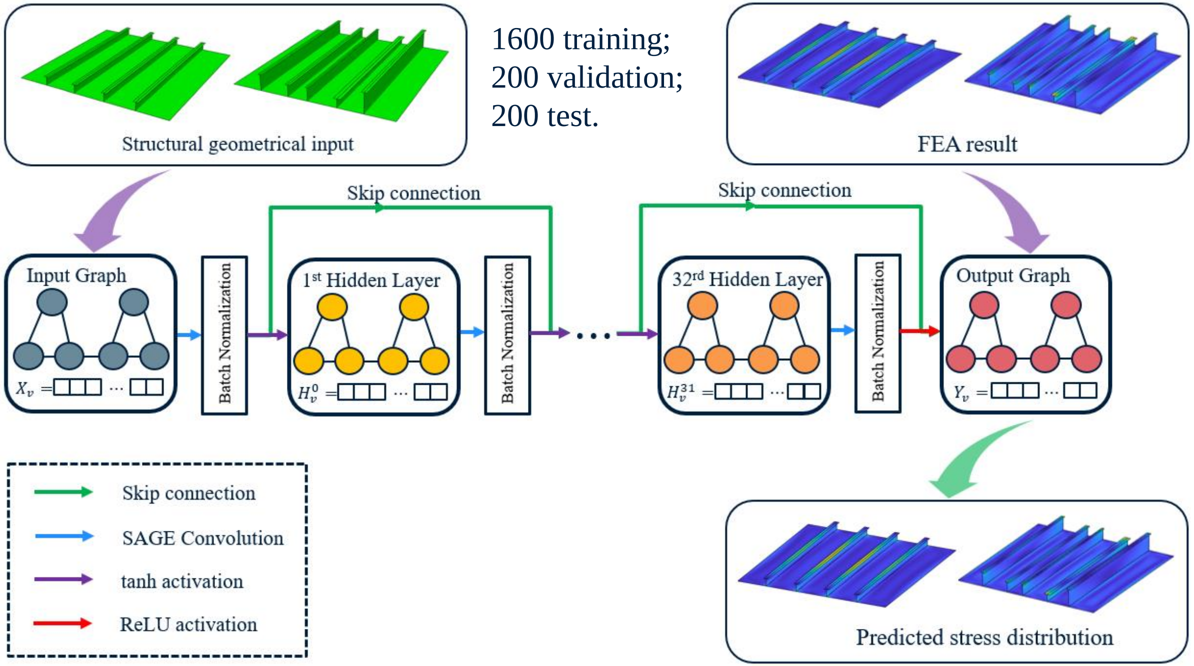
  - Plate edges: fixed or simply supported



  - Stiffener web and flange edges: fixed or simply supported or free



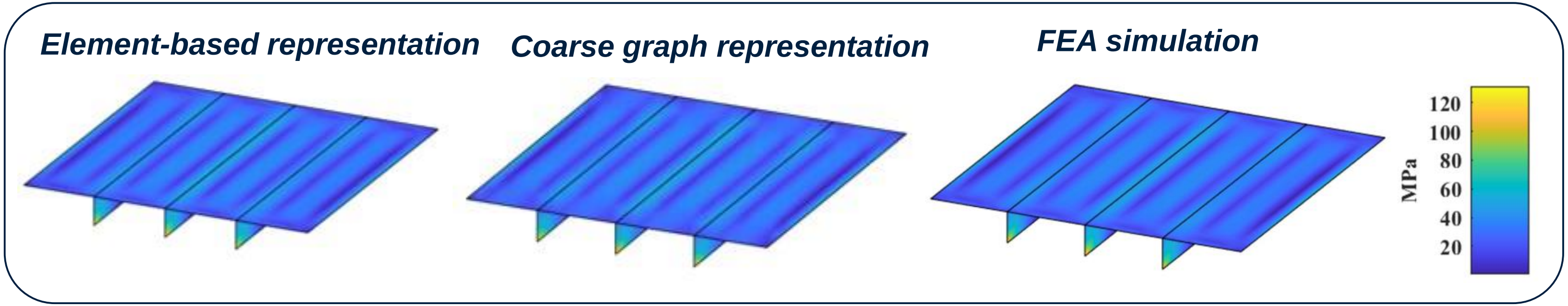
Employed graph neural network model



ENVIRONMENT

- Dataset is obtained using MATLAB & Abaqus
- GNN training is performed based on Python - PyTorch Geometric

Comparison between different graph representations



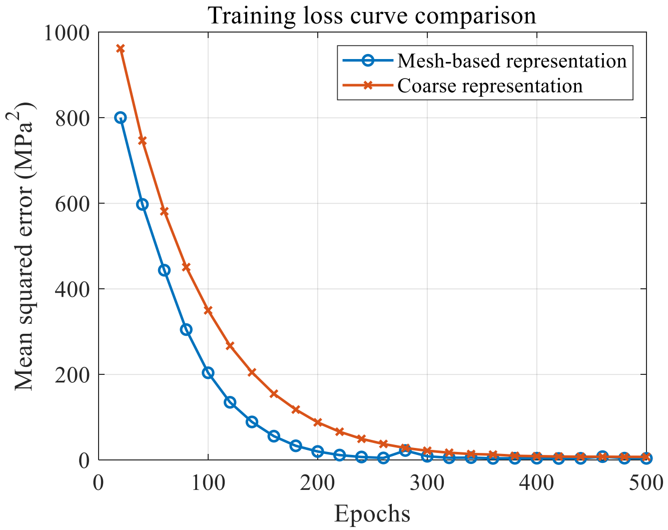
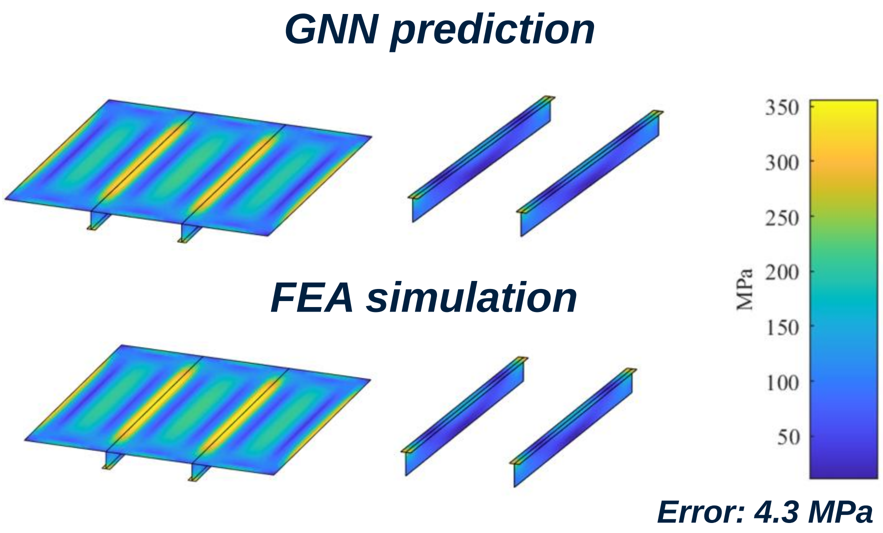
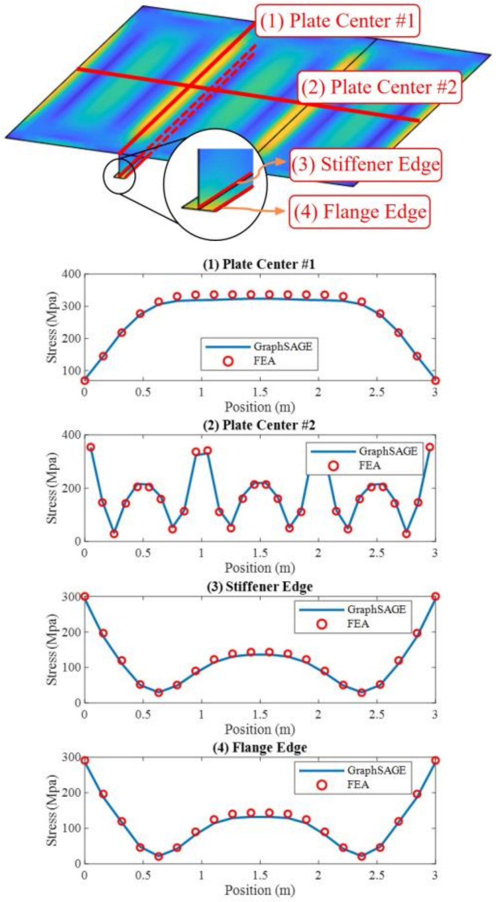


Table. Computation resources comparison for the two graph representations

Category	Element-based representation	*Coarse graph* representation
Time per epoch	6.94 seconds	0.25 seconds
GPU memory	23.4 GB	0.5 GB

GNN results for pressure loading on straight panels



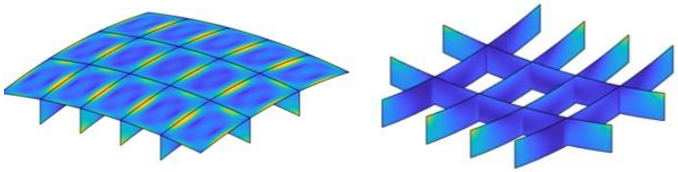


- Plate thickness (mm): 13.03
- Stiffener web thickness (mm): 19.0
- Stiffener web height (mm): 218
- Flange thickness (mm): 6.51
- Flange width (mm): 92.7
- Loading amplitude (MPa): 0.174 Mpa
- BC @ Plate edges: Fixed
- BC @ Stiffener & flange edges: Fixed

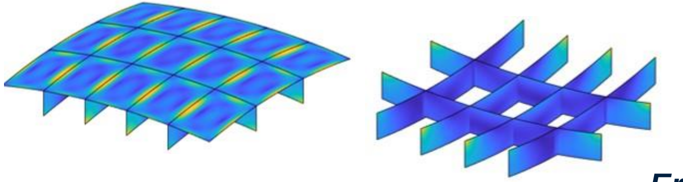
Cai and Jelovica, *TWS*, 2024

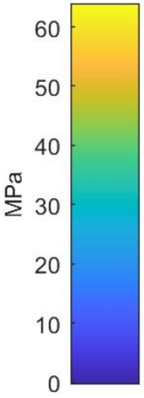
GNN results for pressure loading on curved panels

GNN prediction

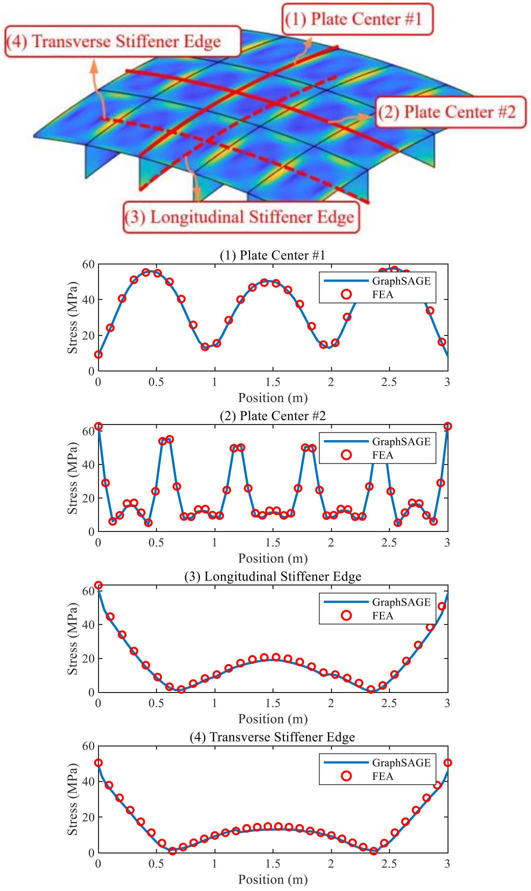


FEA simulation





Error: 1.9 MPa

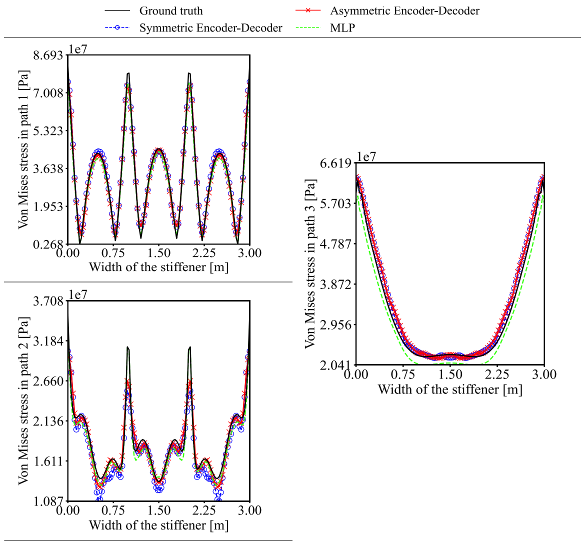


- ➢ Plate thickness (mm): 12.378
- ➢ Longitudinal stiffener web thickness (mm): 7.82
- ➢ Longitudinal stiffener web thickness (mm): 14.6
- ➢ Stiffener web height (mm): 362
- ➢ Panel curvature (1/m^2): 0.013
- ➢ Loading amplitude (MPa): 0.096 Mpa
- ➢ BC @ Plate edges: Simply supported
- ➢ BC @ Stiffener & flange edges: Simply supported

Cai and Jelovica, *TWS*, 2024

CNN results for pressure loaded panel

Parameters	TC1
Material	Linear elastic
B.C	Fixed (Clamped)
Loading	Uniform pressure
Geometrical Parameters	Vary



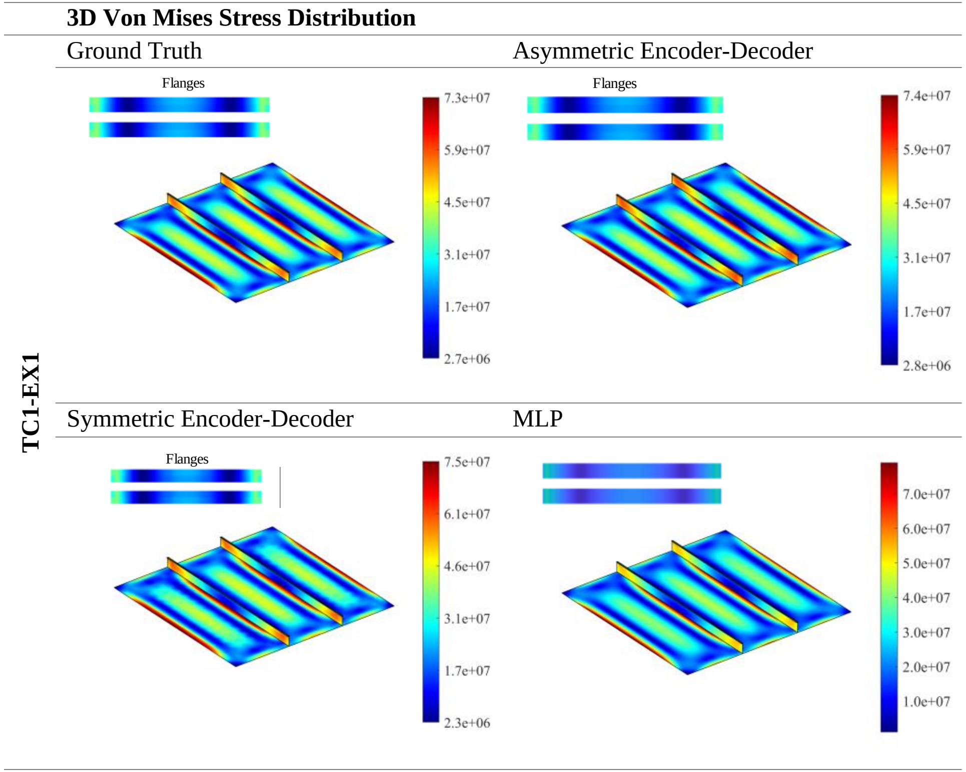
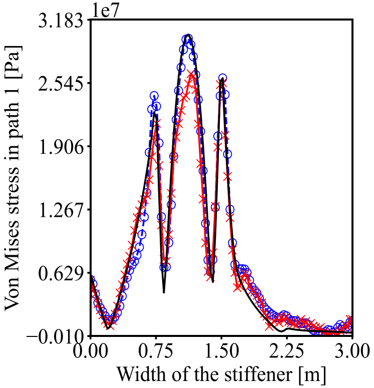
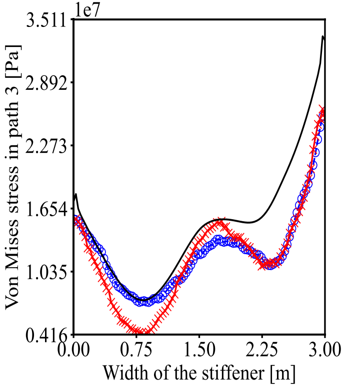


Plate thickness (mm): 17.5, Web thickness (mm): 7.0, Web height (mm): 343.0, Flange width (mm): 99.9, Flange thickness (mm): 18.8, Loading amplitude (MPa): 0.059

CNN results for patch loaded panel

Parameters	TC1
Material	Elastic-plastic
B.C	Fixed (Clamped)
Loading	Patch
Location of the patch	Varies
Geometrical Parameters	Vary





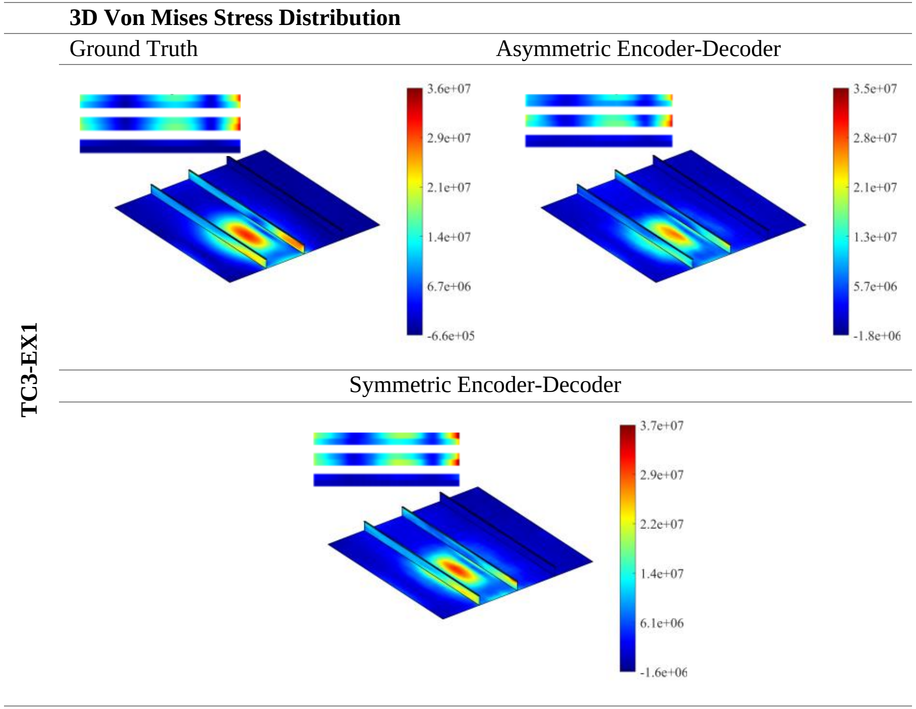


Plate thickness (mm): 18.3, Web thickness (mm): 9.6, Web height (mm): 253.8, Flange width (mm): 128.7, Flange thickness (mm): 6.6, Loading amplitude (MPa): 0.096

Conclusion

- Global multi-objective optimization can be accelerated through the ‘repair’ constraint-handling technique
- Further improvements can be achieved by employing advanced surrogate models in the framework
- Once trained, GNN and CNN models can make predictions in a fraction of a second
- Large dataset is needed for purely data-driven approach
- More effective approaches will be sought in future
- Generalizable and scalable capabilities need to be developed, utilizing principles of structural mechanics