

GRAPH NEURAL NETWORKS FOR ACCELERATED 2D TRUSS OPTIMIZATION

Master of Science dissertation

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by

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Declaration

The work submitted in this dissertation is the result of my own investigation, except where otherwise stated.

It has not already been accepted for any degree, and is also not being concurrently submitted for any other degree.

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Abstract

Structural optimization of skeletal forms plays a crucial role in weight-sensitive applications, but conventional iterative methods often demand significant computational effort, especially under varying design parameters and constraints. This dissertation introduces a novel Graph Neural Network (GNN)-based surrogate model designed for real-time structural optimization, offering a computationally efficient alternative. By representing trusses (composed of pin joints and members) as mathematical graphs, where nodes correspond to joints and edges denote member cross-sectional areas, the GNN predicts topology and size-optimized truss structures based on input parameters such as geometry, loading conditions, and boundary constraints. The model eliminates the need for iterative processes by learning from a dataset of problem definitions and their corresponding optimized solutions, significantly reducing computational costs while maintaining high accuracy. Testing across various initial design domains with node configurations of 24, 45, and 60 demonstrated robust performance. For topology optimization, the recall rate consistently reached unity or near-unity, and the Jaccard similarity index exceeded 0.95 in all cases with 60 nodes trained on 9600 data points, with minor exceptions of 0.94 and 0.87, still indicating reliable predictions. In size optimization, the Mean Absolute Percentage Error and Symmetric Mean Absolute Percentage Error remained below 8% across all results for cantilever and simply supported loading scenarios. It is important to highlight that these highly accurate optimization results were generated using the GNN-based framework, which reduces the computational time by over 95% compared to traditional optimization methods. These results highlight the model's ability to generalize across diverse design scenarios, enabling rapid, accurate, and material-efficient optimization. By offering near-optimal solutions with minimal computational effort, this GNN-based approach holds significant potential for sustainable and resource-efficient structural design across various applications.

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