Developing of an Geometry-aware AI model for Predicting Stress Distribution in Aluminum Wheels under Impact

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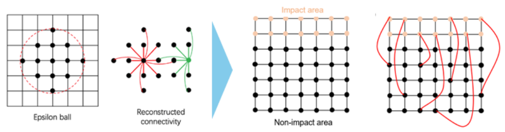
The durability and strength of aluminum wheels are critical factors in vehicle safety, as wheel failure poses a severe threat to occupants. Traditionally, strength prediction relies on finite element analysis (FEA) simulating the 13-degree impact strength test — a standardized method for assessing wheel performance under real-world conditions. However, FEA requires substantial computational cost and time, limiting rapid iteration across diverse wheel designs in early development. Previous AI models using 2D images or 3D voxels failed to accurately predict stress distributions due to insufficient geometric representation. To overcome this, we propose a Graph Neural Network (GNN) framework that directly learns high-fidelity 3D mesh data to predict dynamic impact stress distributions with production-level accuracy.

Unlike preliminary studies using simplified models with only 3,000 to 5,000 nodes, this study utilizes production-level dynamic impact analysis data containing over 200,000 nodes per wheel — up to 100 times larger. While prior studies relied on static analysis, this work adopts dynamic impact analysis results as training data, reflecting real-world development standards. A total of 85 wheel designs were analyzed under 2 to 4 impact load directions, yielding 745 raw datasets extracted from Abaqus ODB files via Python scripts. To optimize learning efficiency, only spoke region nodes — the primary area of concern in impact analysis — were retained in preprocessing, reducing the data size to 2.4% of the original. After augmentation via the Random Edge Connection technique, a final dataset of 580 samples (524 training / 56 test) was constructed with no overlapping wheel geometries. The GNN is based on MeshGraphNets, comprising an encoder, a message-passing module, and a decoder that maps geometric, material, and boundary condition inputs to six stress components and three displacement components per node.

Two algorithmic improvements were applied. First, a Geometry-aware Edge Reconstruction and Augmentation technique was introduced. As mesh density increases, standard message-passing becomes limited in capturing long-range structural dependencies. Rather than uniformly adding edges across all nodes, additional edges were selectively generated between nodes in the Impact zone, where the barrier directly loads the wheel, and the Non-impact zone. This efficiently transmits critical boundary information over long distances while reducing computational cost. By varying the random seed and selection ratio as hyperparameters, training diversity and generalization were further enhanced, contributing an additional 3% improvement in prediction performance. Second, a modified Weighted Loss Function was applied. Since failures predominantly occur at localized regions such as spoke junctions or notch geometries, the loss function was redesigned to impose higher penalties on errors in high-stress concentration zones, yielding a 10% improvement in prediction accuracy.

The model was evaluated on 56 test samples from 8 unseen wheel geometries, achieving a MAPE of 7.0% and a KLD of 0.005 for von Mises stress prediction in the top 20% high-stress regions. A KLD of 0.005 confirms that the predicted stress distribution is nearly identical to the FEA ground truth. Combining Edge and Data Augmentation with N=20 message-passing layers and the AdamW optimizer yielded the best performance of R^2=0.712. The model successfully identified potential failure locations in unseen geometries, demonstrating strong generalization. Compared to conventional FEA, the GNN dramatically reduces computation time while preserving geometric fidelity, making it well-suited for rapid performance screening in early-stage chassis design. Future work includes extending to a time-series GNN, incorporating experimental data, and applying the framework to other chassis components such as suspension arms.



(a) Node Connectivity Reconstruction (b) Improved Node Connectivity Reconstruction

Fig.1 Improved Mesh Reconstruction

$$\text{New loss} = L_2\,(prediction_1, ground\ truth_1) + \boldsymbol{\gamma}\, \boldsymbol{L_2}\,(\boldsymbol{prediction_2}, \boldsymbol{ground\ truth_2})$$

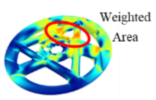


Fig.2 Modified Loss Function and Weighted Region

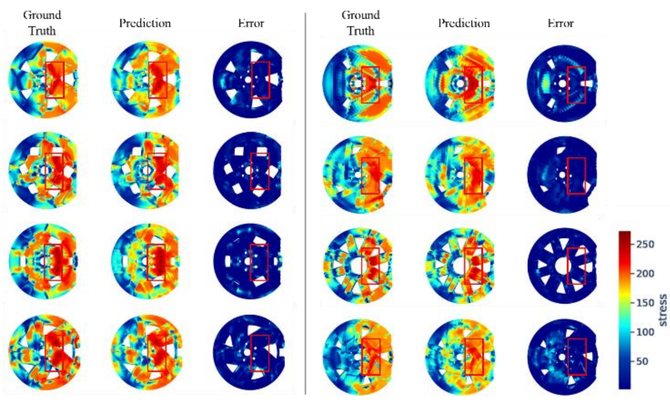


Fig.3 Comparison of Stress Distribution