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Coupling Graph Neural Networks and Finite Element Analysis for Faster Mechanical Stress Prediction

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Abstract: Finite-element analysis (FEA) is the de-facto standard for structural assessment of automotive components, but repeated meshing, boundary-condition setup, and solver runs make design exploration costly and time-consuming. This paper investigates a data-driven surrogate approach that couples graph neural networks (GNNs) with FEA to predict full-field stress distributions on a tractor axle steering knuckle. Historical FEA results from multiple geometries, focusing on variations of the spindle fillet radius, were curated as a training corpus and ingested by Altair Physics AI, a geometric deep-learning framework. The proposed workflow comprises dataset generation from validated FEA studies, GNN training with mean-squared-error loss, and out-of-sample validation on previously unseen geometries. The trained model delivers stress patterns and peak principal stress estimates within approximately ±10% of traditional FEA across the tested cases, while reducing prediction time from minutes–hours to seconds once trained. Learning curves indicate stable convergence with decreasing training and validation losses and mean absolute error (MAE) on the test set of ~6.6 MPa at the critical spindle radius. The results suggest that GNN-based surrogates can accelerate early-stage design iterations and enable broader parametric exploration, provided that new geometries remain inside the trained design space. We discuss dataset design, sources of error, and practical guidance for deploying GNN/FEA surrogates in industrial settings.

Keywords: Finite-element analysis; Graph neural networks; Geometric deep learning; Surrogate modeling; Stress prediction; Steering knuckle

I. INTRODUCTION

Mechanical components such as steering knuckles are traditionally designed via iterative finite-element analysis (FEA) to ensure strength and durability under multi-axial loading. Although robust, repeated FE studies for shape changes (e.g., spindle fillet radius) are computationally expensive, limiting the breadth of optimization in early design. Recent advances in machine learning, particularly geometric deep learning on meshes/graphs—offer surrogates that learn mappings from shape and boundary conditions to stress responses, drastically reducing evaluation time once trained. Building on this idea, we study a GNN-based surrogate trained from historical FEA of a tractor axle as shown in Figure 1, steering knuckle to rapidly predict stress fields and peak principal stress at the critical spindle radius.

Figure 1. Tractor axle with steering knuckle (schematic)

In this study, our aim is to design a Machine learning based model for the FEA process for automobile components. For a given design space, to create a data-driven learning-based alternative model for the simulation process. The benefit of creating a parallel faster evaluation of other design points by a trained model, and it will speed up the whole design decision process. These learning models are then can be used for the outer optimization loop,

The field of FEA is constrained by the length of time needed for modeling, the expense and length of time required for computing to solve the problem, and the necessity of considerable expert participation to understand the findings. These problems are frequently solved using ML approaches, according to evidence from ML applications.

II. MATERIALS AND METHODS

A. Problem Formulation

The steering knuckle supports wheel-end bearings and reacts steering and drive torques. Stress concentrations at the spindle fillet radius govern design as depicted in Figure 2 & Figure 3. In a baseline workflow, pl refer to Figure 4, CAD updates are meshed and solved via static structural FEA; peak stress is compared to material allowable, and geometry is iterated. Our goal is to learn a surrogate that maps geometry (with varying spindle radius and local features) and loading to predicted full-field stress and peak principal stress, enabling rapid screening while preserving acceptable accuracy.

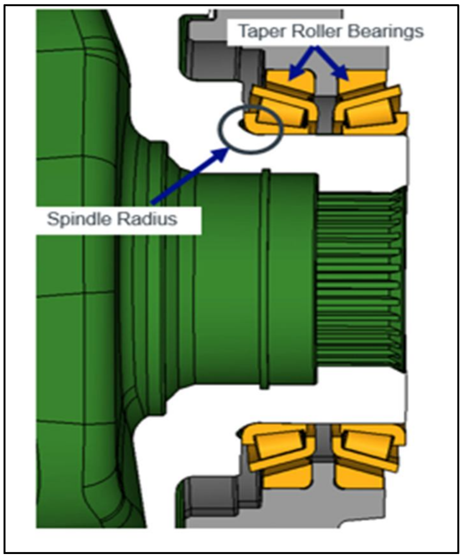


Figure 2. Steering knuckle with tapered roller bearings (schematic)

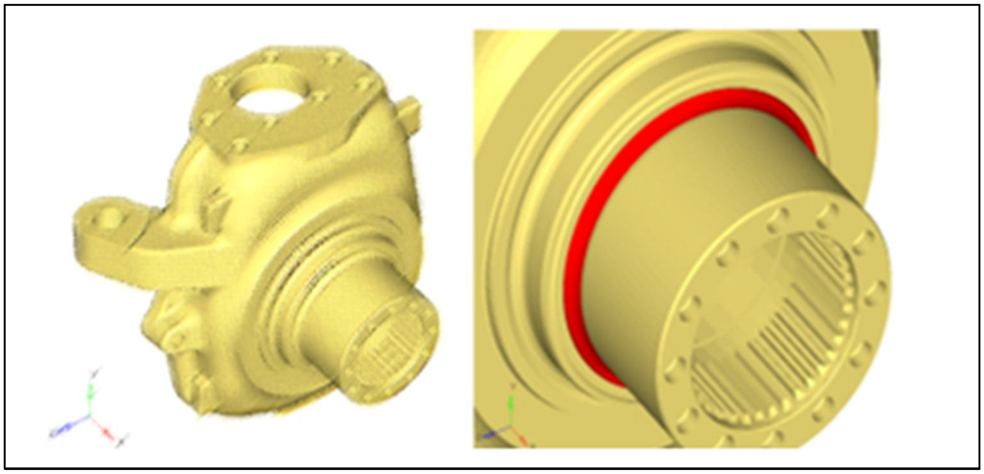


Figure 3. Steering knuckle highlighting spindle radius (critical region)

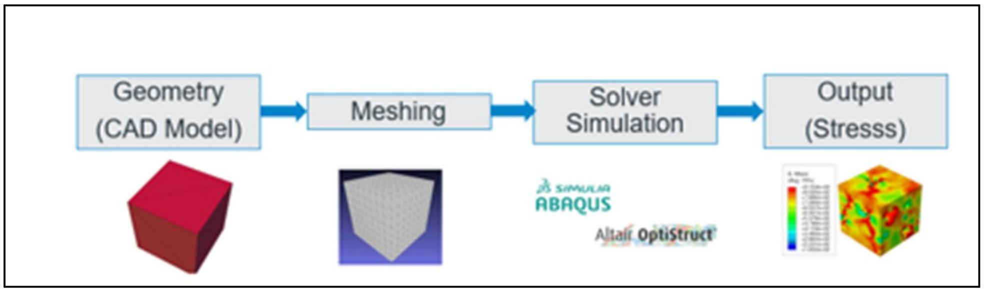


Figure 4. Traditional FEA workflow

In this work, our goal is to create a deep learning model for this entire simulation process for a large class of problems & predict the stress range coming on the new designed knuckle spindle radius. The motivation for creating a deep learning model in such way that it can interpolate or predict the numerical simulation output at a very low cost in terms of time for solving using trainable models. Once trained model can replace the numerical simulators for outer loop optimization operations. The expected benefit is the ability to design the steering knuckle on a given requirement at a very small computational time for a range of problems. The class of problem is defined by the design space in our case design parameter is spindle radius. For learning a model, we first create a design space. Our design space consists of the maximum width & height of our shell boundary of steering knuckle depth. Refer Figure 5.

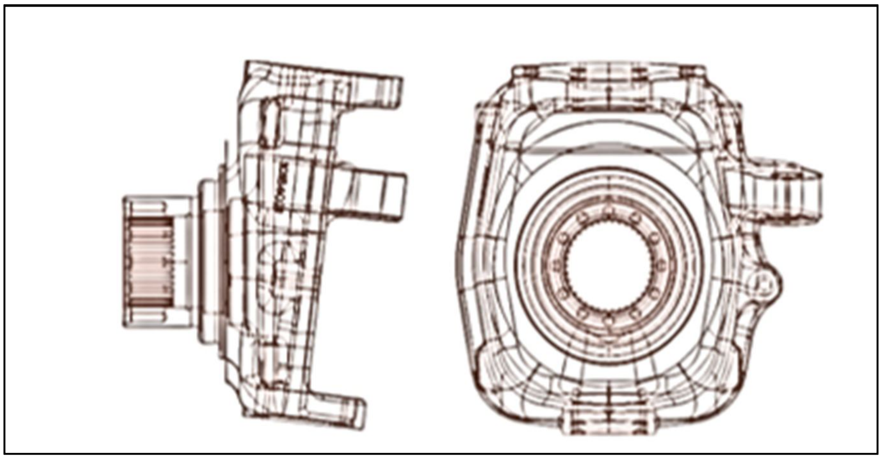


Figure 5. Design space for steering knuckle (bounds and parameters)

B. Geometric Deep Learning and Graph Neural Networks

We utilize Altair Physics AI to train a GNN on mesh/graph representations of the knuckle. GNNs perform message passing over nodes/edges to aggregate local geometric and boundary-condition information into latent features, which are then decoded into per-element stress estimates. This paradigm naturally respects mesh connectivity and can generalize within a bounded design space. Figure 6 shows the simple workflow of Machine Learning model.

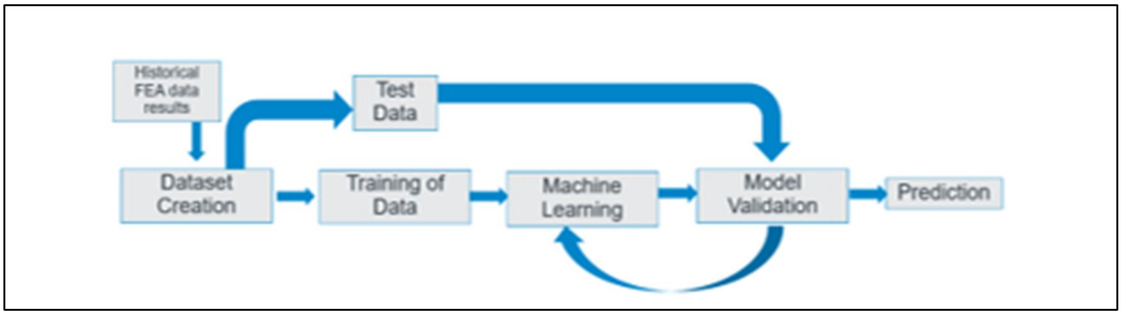
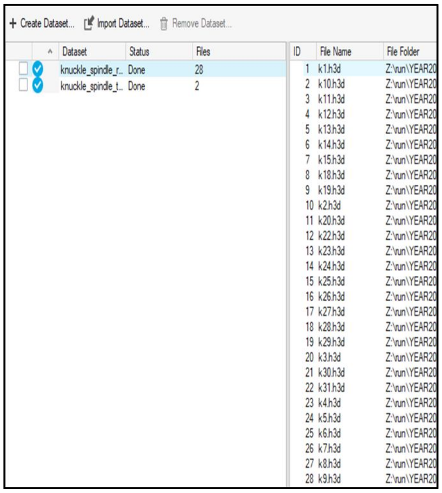


Figure 6. Workflow of the AI/GNN surrogate model

C. Dataset Generation

Historical FEA studies of steering knuckles with varied spindle radii (e.g., circular, elliptical, and blended fillets) form the training set. For each design, validated boundary conditions and material data were used to compute principal stress fields. Datasets shown in Figure 7. include mesh topology, node/element attributes, and scalar targets (peak principal stress at the spindle radius).



	Dataset	Status	Files
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☐ ✓	knuckle_spindle_t...	Done	2

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3	k11.h3d	Z:\run\YEAR20
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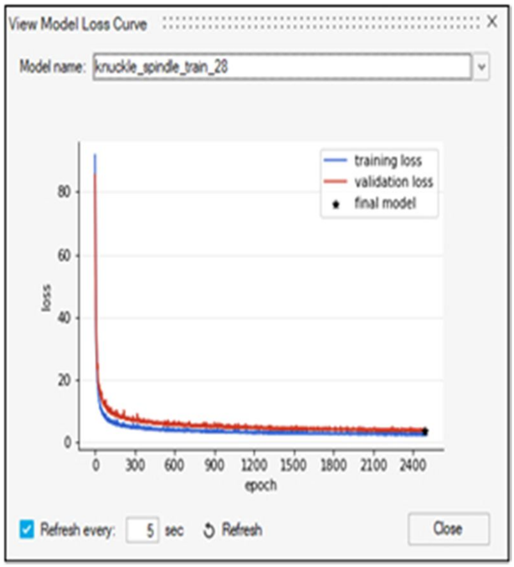
Figure 7. Dataset assembly in Physics AI

D. Training Protocol

Models were trained using mean-squared-error loss with standard train/validation/test splits. Convergence was assessed via loss histories; we observed decreasing and overlapping training/validation losses after ~20 epochs, indicating stable fitting. Hyperparameters were selected to balance accuracy and overfitting risk. Refer to figure 8.



Model name: knuckle_spindle_train_28

☑ Refresh every: 5 sec

Figure 8. Training and validation loss histories

E. Validation and Testing

Two out-of-sample knuckle geometries, with spindle radii do not present in the training set, were used for validation. For both cases, the model predicted full-field stress patterns closely aligned with FEA, with mean absolute error (MAE) of ~6.6 MPa at the critical radius. Refer to Figure 9.

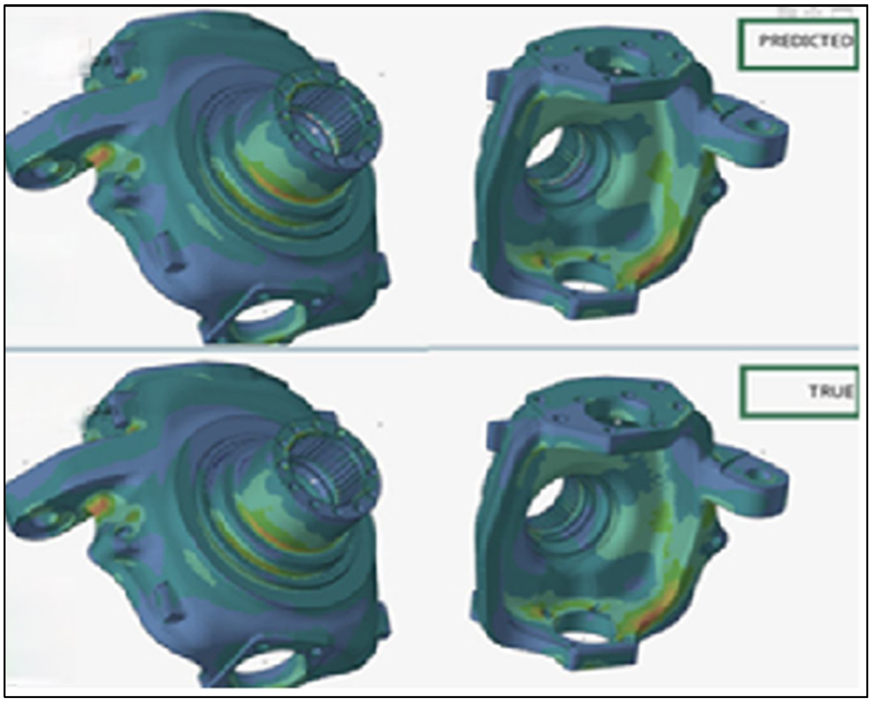


Figure 9. True & Predicted FEA Stress for Steering Knuckle (12 mm radius)

III. RESULTS AND DISCUSSIONS

The trained GNN surrogate reproduced the spatial distribution of principal stresses over the knuckle and captured peak values within ±10% of FEA for the tested designs. Once trained, inference required seconds, enabling rapid what-if evaluation across candidate radii and blends. Refer to Figure 10. Performance depends on (i) representativeness of the training set across the intended design space, (ii) mesh quality and consistent boundary conditions, and (iii) appropriate targets (e.g., per-element stresses and critical metrics). Extrapolation outside the design space can degrade accuracy; periodic retraining with new FE studies is recommended. While FEA remains essential for certification and corner cases, the surrogate can offload routine iterations and guide optimization.

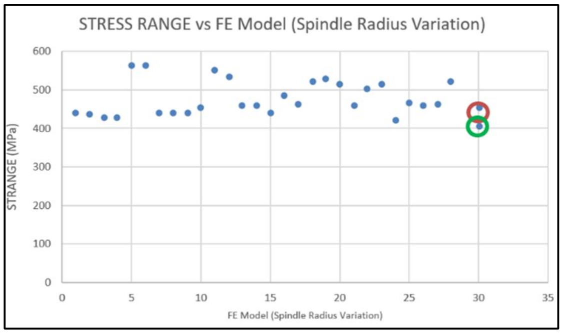


Figure 10. Stress Comparison for predicted results by GNN (Green) vs Traditional FEA (Red)

IV. CONCLUSIONS

A GNN-based surrogate trained on historical FEA of a steering knuckle can predict stress fields and peak principal stress with engineering-level accuracy while drastically reducing evaluation time. The approach supports accelerated early-stage design and broader parametric exploration, provided that new geometries remain within the trained design space. Future work includes multi-physics targets, uncertainty quantification, and active-learning schemes for automated dataset expansion.

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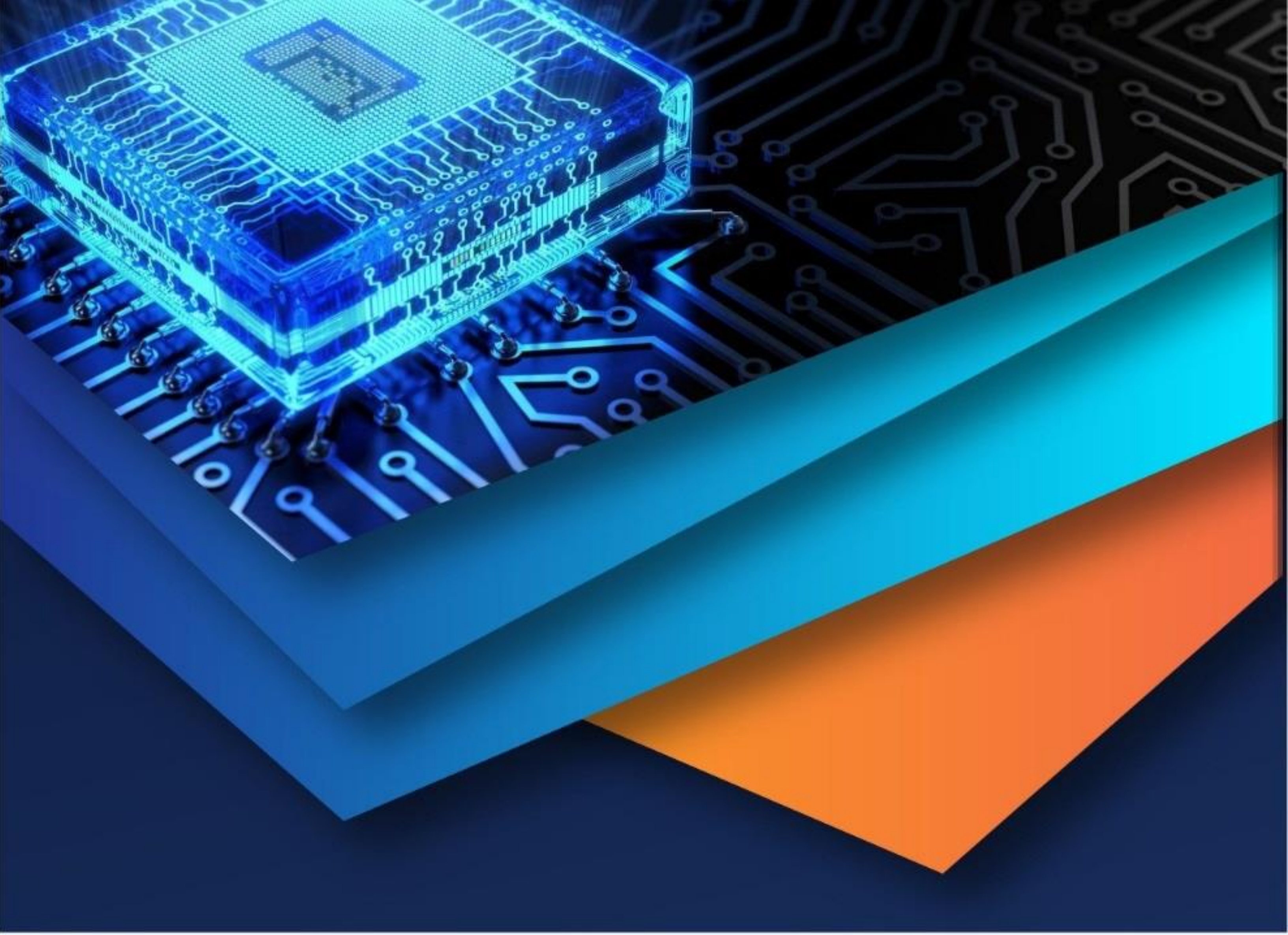

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