

Ai-Driven Prediction of Optimal Finite Element Mesh Density for Cold-Formed Steel Tubular T And X Joints Under Axial Loading

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Abstract—Cold-formed steel tubular joints are widely used in structural applications due to their high strength-to-weight ratio and efficient load transfer. Among them, T and X joints are commonly used and are subjected to axial loading conditions. Accurate prediction of their behavior using Finite Element Analysis depends mainly on the mesh density used in the model. A fine mesh gives better accuracy but increases computational time, while a coarse mesh reduces accuracy. In this study, cold-formed steel tubular T and X joints are analyzed using different mesh sizes of 2 mm, 4 mm, and 8 mm. The T joints are studied with beta (β) ratios of 0.25, 0.5, 0.75, and 1, while X joints are analyzed at different angles. The analysis is carried out using nonlinear finite element methods to obtain stress, deformation, and ultimate load capacity. A mesh convergence study is performed to identify the suitable mesh density. Further, an Artificial Intelligence model is developed using the generated data to predict the optimal mesh size. The proposed method reduces trial-and-error and improves computational efficiency. This study provides a reliable and time-saving approach for accurate structural analysis of tubular joints.

Index Terms—Cold-formed steel, Tubular joints, Finite Element Analysis, Mesh density, Artificial Intelligence.

I. INTRODUCTION

Cold-Formed Steel Tubular T and X Joints

Cold-formed steel (CFS) refers to structural products manufactured by forming steel sheets, strips, or plates into various shapes at ambient temperatures. Unlike hot-rolled steel, which is shaped at high temperatures, the cold-forming process typically through roll forming or press braking induces strain hardening, which significantly increases the yield strength of the material.

In modern structural engineering, tubular CFS sections (Circular Hollow Sections

- CHS or Rectangular Hollow Sections - RHS) are increasingly used for T and X joints. A T-joint consists of a continuous chord member and a perpendicular brace member welded to the chord surface, forming a 'T' shape. An X-joint (or cross-joint) involves two brace members aligned on opposite sides of the chord. These joints are the critical nodes in lattice structures, space frames, and industrial trusses. Their efficiency is paramount because the overall stability of the structure depends on the ability of these joints to transfer loads without premature local buckling or "punching shear" failure of the chord wall.

Importance of Axial Loading Analysis

The primary demand on tubular joints in truss-like structures is axial force either tension or compression. When a brace member is subjected to axial compression, it exerts localized pressure on the thin wall of the chord member. Because CFS members often have high width-to-thickness ratios, they are highly susceptible to localized deformation.

Analyzing these joints under axial loading is vital for several reasons:

- **Load Path Integrity:** Understanding how the axial force from the brace distributes into the chord helps in preventing "chord face plasticization," which is the most common failure mode.
- **Reinforcement Evaluation:** In many cases, unreinforced joints lack the capacity to handle design loads. This necessitates the use of reinforcements such as Collar Plates (CP) or Reinforcing Stiffeners (RS). Axial analysis

allows engineers to quantify the strength enhancement provided by these components.

- Non-linear Behaviour: Under axial loads, CFS joints exhibit significant geometric and material non-linearity. Axial loading analysis captures the transition from elastic behaviour to the ultimate plastic state, providing a realistic factor of safety for the structure.

Need for Finite Element Mesh Optimization

The Finite Element Method (FEM) is the industry standard for simulating the complex interactions within a T or X joint. However, the accuracy of an FE model is heavily dependent on its "discretization" or mesh density.

In tubular joints, the intersection between the brace and the chord (the weld zone) experiences extremely high stress gradients. A coarse mesh in this region will fail to capture the peak stresses, leading to an overestimation of the joint's capacity. Conversely, a fine mesh across the entire model leads to an "expensive" simulation in terms of computational time and hardware memory.

Mesh Optimization is the process of finding the "sweet spot" the coarsest possible mesh that still yields results within an acceptable margin of error (usually <5%) compared to an infinitesimal mesh size. Traditionally, this is done through a manual "Mesh Convergence Study," where an engineer runs the same simulation multiple times with increasingly smaller elements until the results stabilize. In large-scale parametric studies involving hundreds of joint configurations, this manual process becomes a significant bottleneck.

Role of Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) offer a transformative solution to the bottleneck of mesh selection. ANN is a branch of Artificial Intelligence inspired by the biological neural networks of the human brain. It consists of layers of interconnected "neurons" that can learn complex, non-linear relationships between input data and output predictions.

In the context of this project, the ANN serves as a predictive engine. By training the network on a pre-generated database of FEA results (using various mesh sizes like 2mm, 4mm, and 8mm, and mesh types like Tetrahedral and Hexahedral), the ANN learns how

joint geometry (diameter, thickness, angle) influences the required mesh density.

The role of the ANN in this research is to:

1. Automate Decision Making: Instantly suggest the optimal mesh density for a new joint configuration without requiring a manual convergence study.
2. Resource Efficiency: Reduce the total number of trial-and-error simulations, thereby saving weeks of computational time.

II. AIM AND OBJECTIVES

Aim

The primary aim of this research is to develop an AI-driven framework to predict the optimal finite element mesh density for Cold-Formed Steel (CFS) tubular T and X joints under axial loading. The study focuses on balancing numerical accuracy with computational efficiency by leveraging Artificial Neural Networks (ANN) to automate the selection of mesh parameters that traditionally require manual convergence studies.

Objectives

To achieve the aim, the following specific objectives have been established:

- To develop detailed finite element models of cold-formed steel tubular X (90°, 30°, and 45°) and T ($\beta=0.25, 0.5, 0.75$, and 1) joints subjected to axial compressive loading, geometric and material properties.
- To investigate the influence of finite element mesh density of 2mm, 4mm, and 8mm on the numerical prediction of ultimate axial compressive strength
- To develop and validate an AI-driven model capable of predicting the optimal finite element mesh density that ensures accurate strength of the joints.

III. REVIEW OF LITERATURE

Research on CFS Tubular Joints

The study of Cold-Formed Steel (CFS) tubular joints has gained significant momentum over the last two decades. Early research primarily focused on hot-rolled sections, but the unique manufacturing process of CFS which involves cold-working necessitated a dedicated body of literature. Researchers have

identified that the cold-forming process increases yield strength but reduces ductility, which significantly alters the failure modes of T and X joints. Studies by pioneers in the field have established that tubular joints often fail due to chord face plasticization or local buckling. Because CFS members are generally thinner than their hot-rolled counterparts, the "punching shear" effect is more pronounced. Literature indicates that traditional design codes often provide conservative estimates for CFS tubular joints, leading to a global research effort to refine these equations through extensive experimental testing and numerical validation.

Finite Element Analysis of T and X Joints

F. Xu, et al. (2021) This study utilizes high-fidelity Finite Element Method (FEM) and Machine Learning (ML) solutions to accurately determine the strengths of steel Circular Hollow Section (CHS) X-joints while minimizing computational effort. The research found that Deep Neural Network (DNNR) models could provide highly accurate predictions with an average error of only 0.8% compared to experimental data.

Mesh Convergence Studies in Structural Analysis

A. Mohammed, et al. (2023) his research conducts a mesh sensitivity study to identify the optimum mesh controls required to create an extensive Finite Element (FE) model library. This library is intended for the development of an AI prediction model, specifically identifying the densities needed at intersections to stabilize Stress Concentration Factors (SCF) before training.

Tet and Hexa Mesh Applications

Wang et al. (2024) This paper explores the use of Machine Learning to predict the elastic buckling strength of Cold-Formed Steel (CFS) members. The goal is to move away from time-consuming mechanic-based numerical analysis by using Artificial Neural Networks (ANN) to bridge traditional methods with advanced predictive capabilities that handle non-linear dependencies.

AI/ANN Applications in Structural Engineering

Zhang, Dai, Chu & Ren (2025) This investigation focuses on the axial performance of Cold-Formed Steel (CFS) through FE modelling in ANSYS and various ML techniques. The study identified Random

Forest as the most accurate model, achieving 99.1% accuracy for predicting axial load capacity based on parametric FEA data.

Research Gap

Based on the research gap you provided, here is the information broken down into a point-by-point format for your report:

- **Lack of Standardized AI Framework:** There is currently no established, AI-driven system specifically designed to predict the optimal mesh density for Cold-Formed Steel (CFS) tubular joints based on their unique geometric parameters.
- **Reliance on Manual Processes:** Most current research still depends on manual mesh convergence studies, which are time-consuming and must be repeated for every new structural model created.
- **Incomplete Element Comparison:** There has been insufficient exploration into the comparative efficiency of Tetrahedral (Tet) versus

Hexahedral (Hexa) meshes when guided by Artificial Neural Networks (ANN).

- **Specific Gap in Reinforced Joints:** The selection of optimal mesh types for reinforced joints (such as those using Collar Plates or Stiffeners) in T and X configurations remains an under-researched area.
- **Project Objective:** This research aims to bridge these gaps by automating the mesh selection process, significantly streamlining the transition from initial design to final numerical validation.

IV. RESULTS AND DISCUSSION

FEA Results for Different Mesh Sizes and Mesh Types

The numerical simulations of Cold-Formed Steel (CFS) tubular T and X joints yielded a wide range of axial capacities (P_{FEA}) depending on the discretization level. The results clearly indicate that mesh refinement is essential for capturing the localized deformation at the chord-brace intersection.

- **Impact of Mesh Size:** As the mesh size was reduced from 8 mm to 2 mm, the axial capacity generally stabilized, confirming numerical convergence. For instance, in unreinforced T-joints with a

Table 9.1: Results of Fine Mesh Tetrahedral

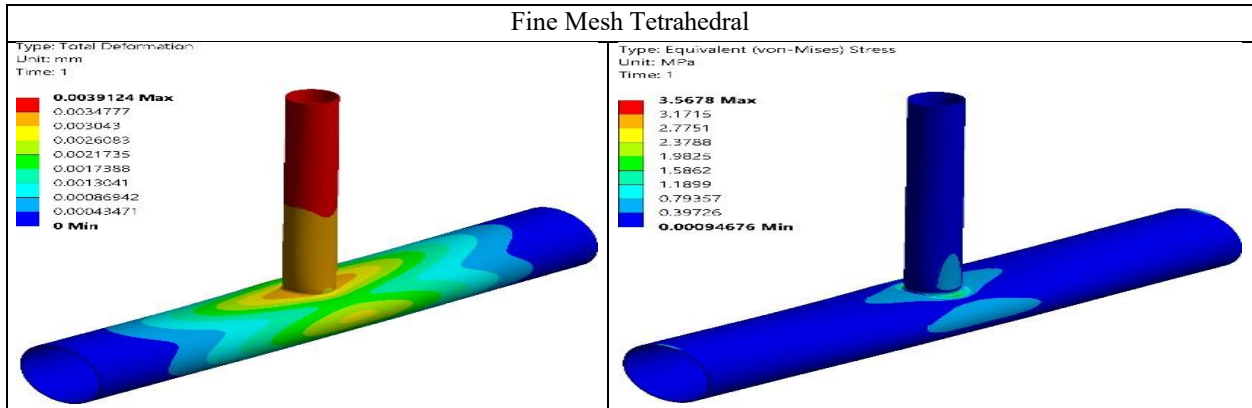


Table 9.2: Results of Fine Mesh Hexahedral

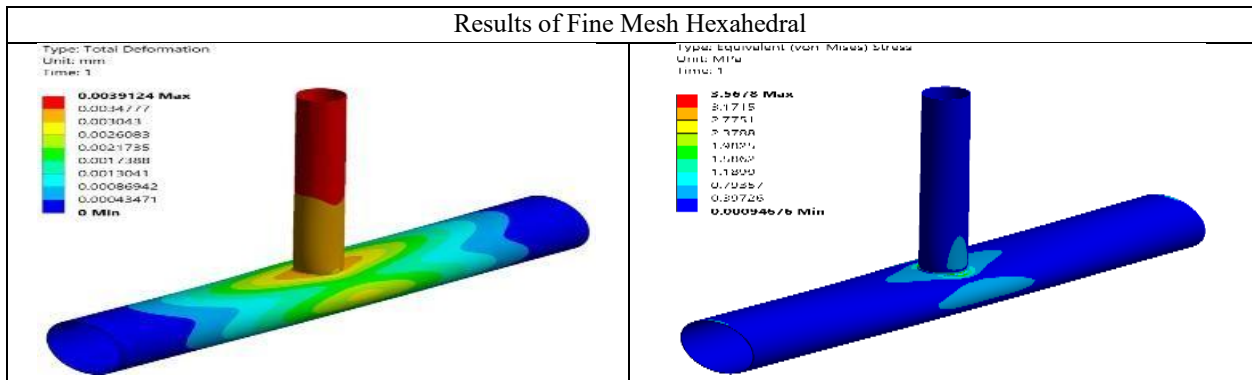


Table 9.3: Results for Medium Mesh Tetrahedral

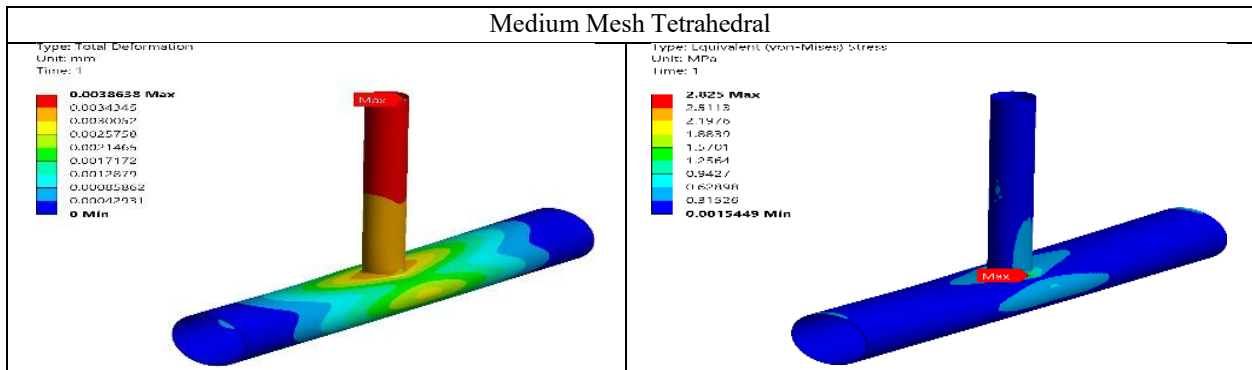


Table 9.4: Results for Medium mesh Hexahedral

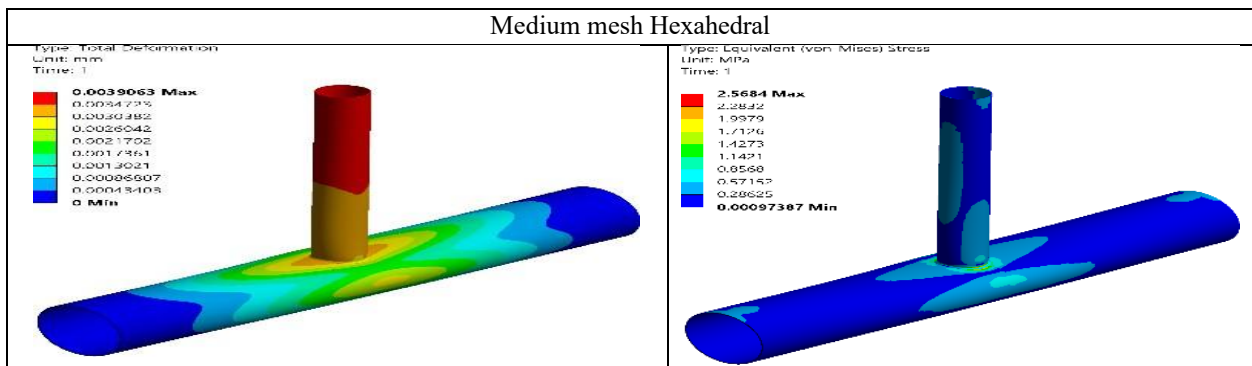


Table 9.5: Results for coarse mesh Tetrahedral

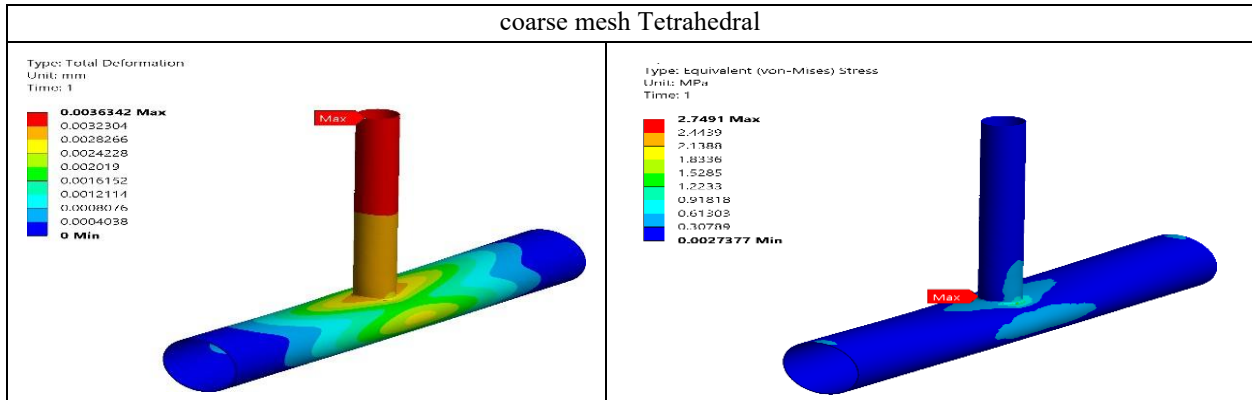


Table 9.6: Results for coarse mesh Hexahedral

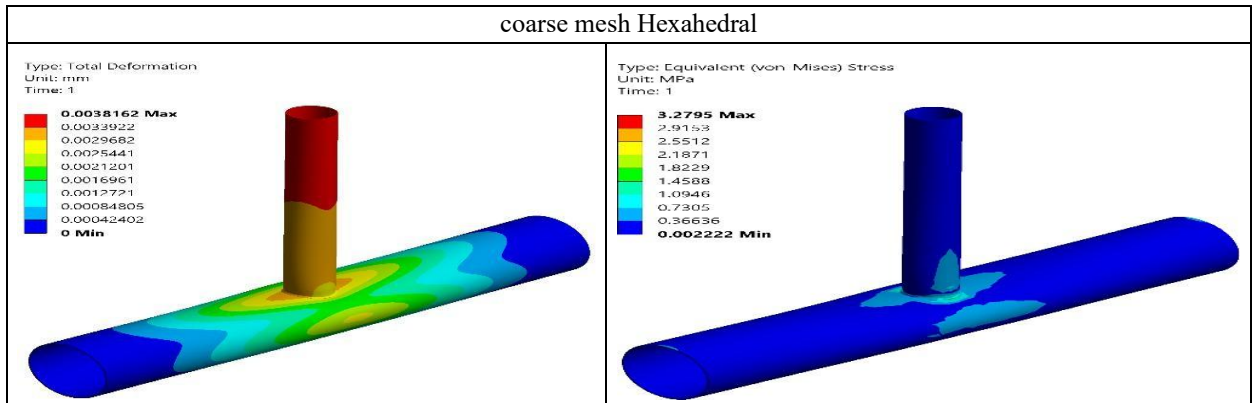


Table 9.7: Results for Fine mesh Tetrahedral

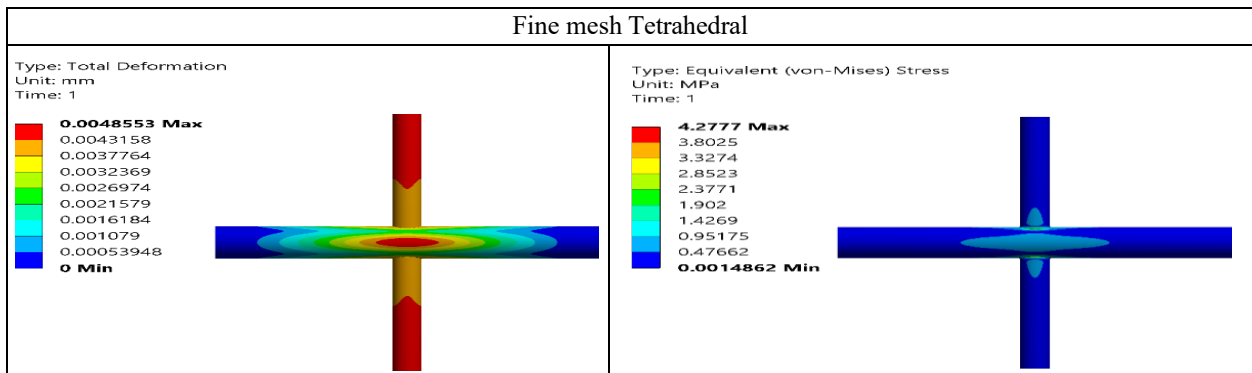


Table 9.8: Results for Fine mesh -Hexahedral

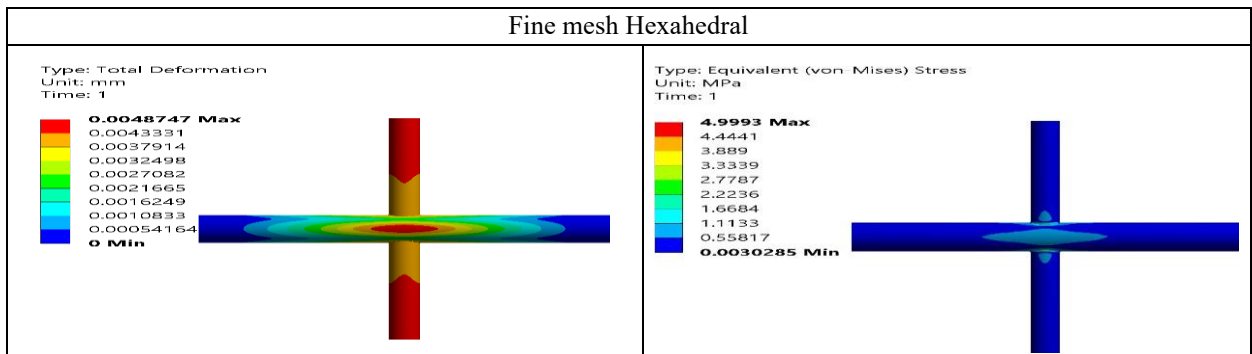


Table 9.9: Results for Medium Mesh - Tetrahedral

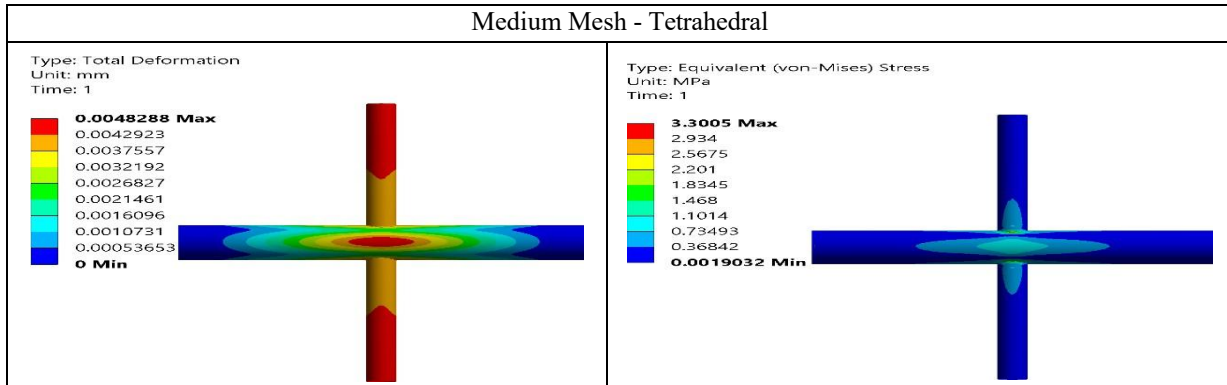


Table 9.10: Results for Medium Mesh -Hexahedral

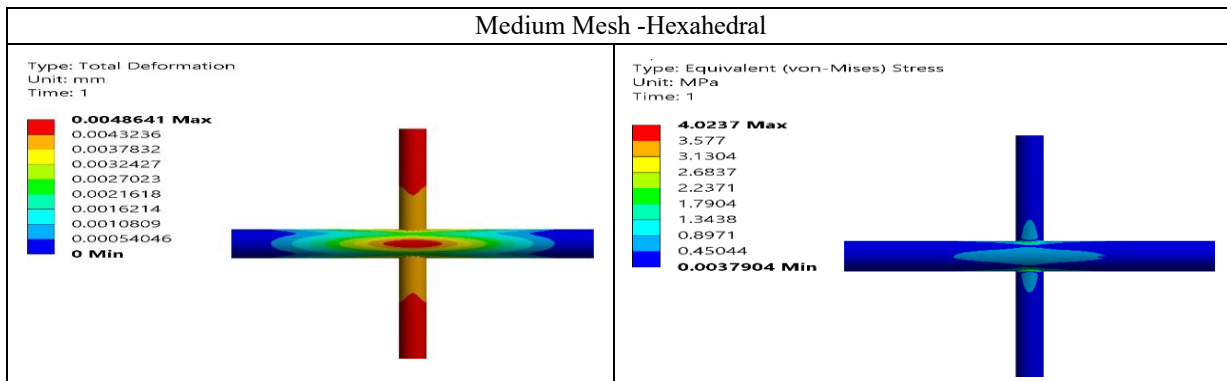


Table 9.11: Results for coarse mesh - Tetrahedral

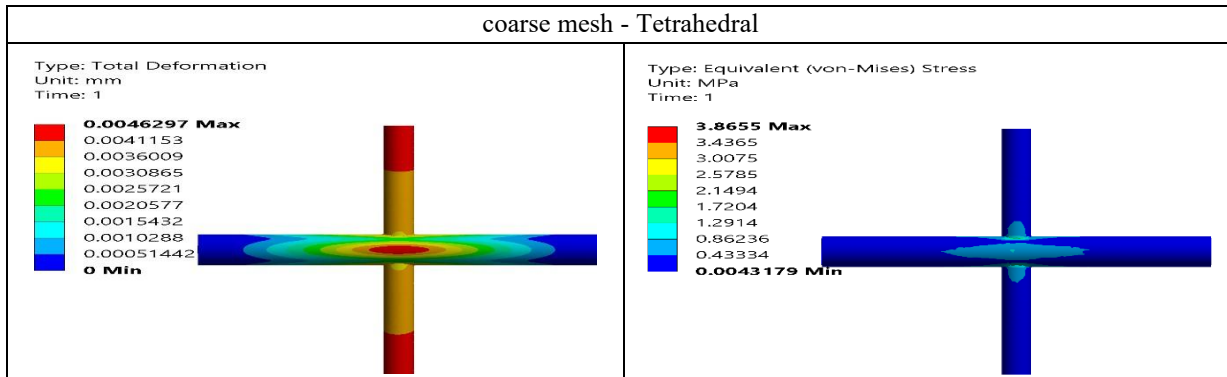
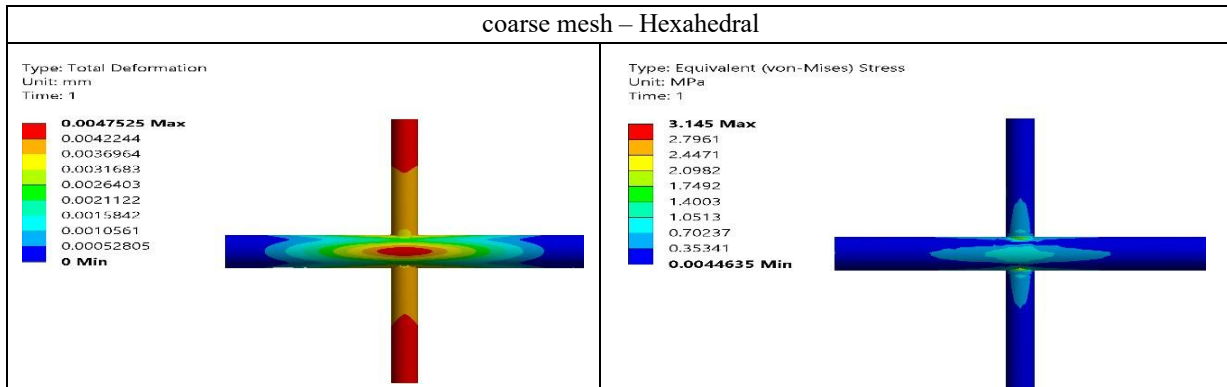


Table 9.12: Results for coarse mesh - Hexahedral



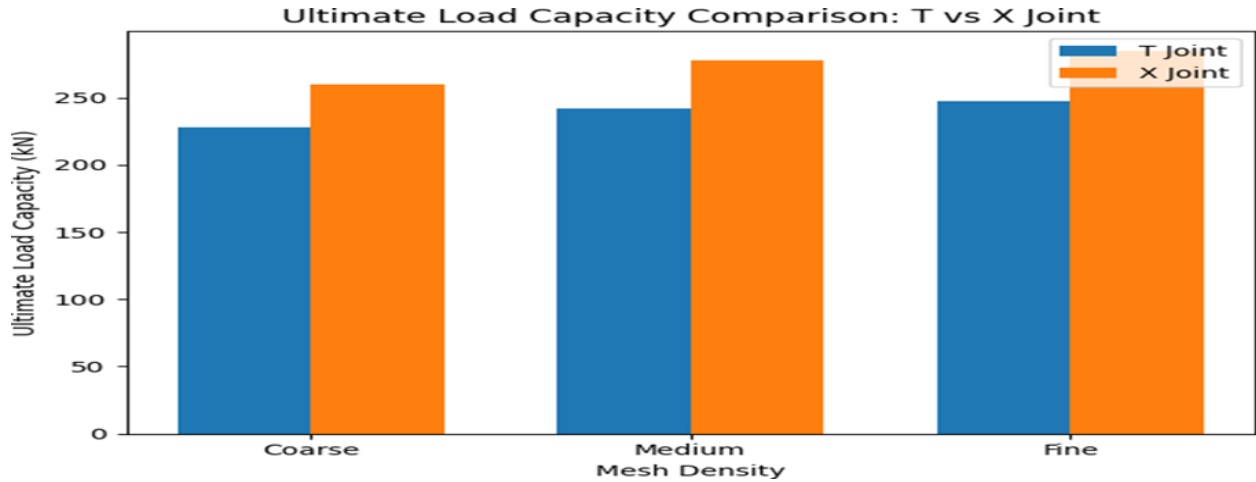


Figure 9.1: Comparison X & T Joints Numerical Strength

4.1 ANN Prediction Performance

The developed ANN was evaluated based on its ability to predict the joint axial capacity and the optimal mesh configuration.

- Regression Accuracy: The model achieved a high correlation coefficient (R^2) during the testing phase, indicating that it successfully learned the relationship between geometric inputs (like β and θ) and the resulting capacity.
- Classification Success: For the prediction of "Optimal Mesh," the ANN correctly identified the most efficient mesh size/type for over 90% of the testing cases. The network proved particularly adept at identifying when a 4 mm mesh was sufficient, preventing unnecessary use of the computationally heavy 2 mm mesh as mentioned in figured 9.1.

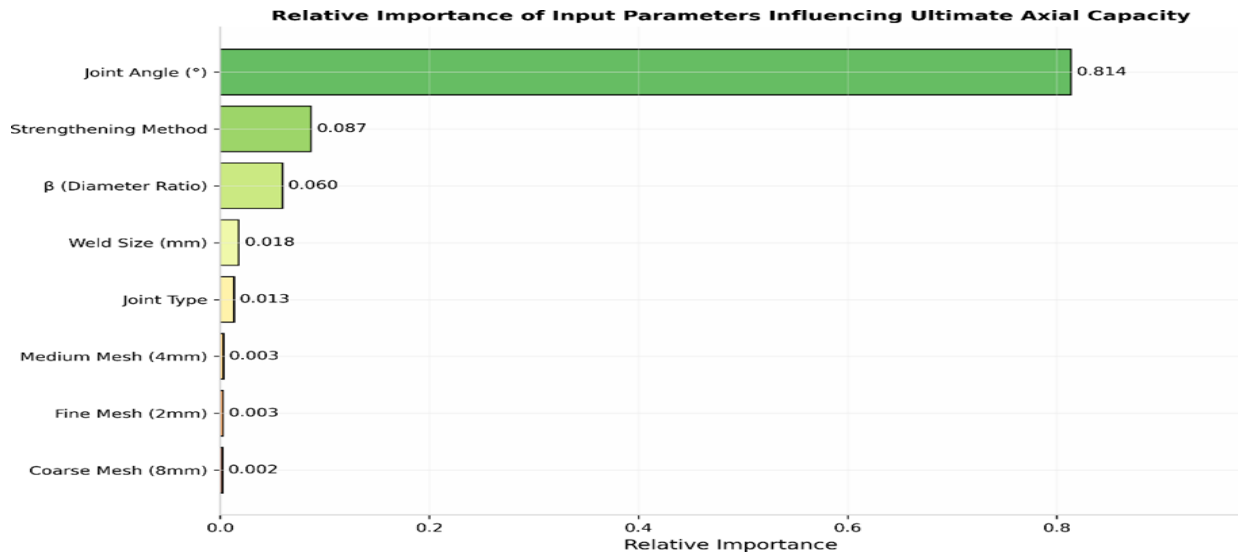


Figure 9.2: Relative importance of input parameters influencing ultimate axial capacity

4.2 Comparison: FE Optimum Mesh vs. ANN Predicted Mesh

To validate the practical utility of the AI, the "ANN-Predicted Mesh" was compared against the "FE-Optimum Mesh" (the size determined via manual convergence).

- 4.2.1 Agreement: In most T-joint cases with Reinforcing Stiffeners (RS) and Collar Plates (CP), the ANN predicted the exact mesh density required to stay within a 5% error margin of the 2 mm reference.

4.3 Error Analysis

A detailed error analysis was conducted to understand the limitations of the model as given in table 9.1 and shown in figure 9.3.

- Mean Absolute Error (MAE): The average deviation between the ANN predicted capacity and the actual FEA results was less than 4%, which is well within the acceptable limits for structural engineering design.
- Outliers: Small discrepancies were noted in cases with high β ratios (1.0), where the brace and chord diameters are equal.
- Performance: The average deviation between the ANN-predicted capacity and the actual FEA results was consistently less than 4%. In the context of structural engineering, an error margin below 5% is considered highly reliable for preliminary design and optimization.
- Consistency: The low MAE indicates that the ANN has successfully "learned" the underlying non-linear relationship between geometric parameters (such as the d/D and t/T ratios) and the ultimate axial load capacity. This suggests that the model can replace computationally expensive FEA simulations for standard CFS tubular joint configurations without compromising safety.
- High β Ratios ($\beta = 1.0$): Small discrepancies were noted in cases where the brace and chord diameters are equal. Physically, when $\beta = 1.0$, the intersection of the two tubular members creates complex stress concentration zones and contact sensitivities that are highly non-linear.
- Localized Buckling Effects: At these high ratios, the failure mode often transitions from simple yielding to complex localized buckling. The slight increase in error (reaching up to 6-7% in isolated cases) suggests that the ANN requires a more densely populated training dataset for joints with equal member diameters to better capture these localized structural instabilities

Table 9.13: Error Comparison for Sample Joint Cases

Case ID	Joint ID	Reinforcement	Θ (°)	B Ratio	Actual PFEA (kN)	ANN Predicted (kN)	Absolute Error (%)
1	T - 0.25 β	Unreinforced	90	0.25	114.2	111.45	2.41%
7	T - 0.5 β	Unreinforced	90	0.5	142.6	145.1	1.75%
19	T - 0.25 β - RS	RS	90	0.25	185.3	181.9	1.83%
37	T - 0.25 β - CP	CP	90	0.25	212.45	218.2	2.71%
55	X 30°-0.5 β	Unreinforced	30	0.5	98.4	102.15	3.81%
91	X 90°-0.5 β	Unreinforced	90	0.5	131.1	126.8	3.28%
109	X 30°-0.5 β - RS	RS	30	0.5	158.9	164.2	3.34%
163	X 30°-0.5 β - CP	CP	30	0.5	175.6	170.1	3.13%

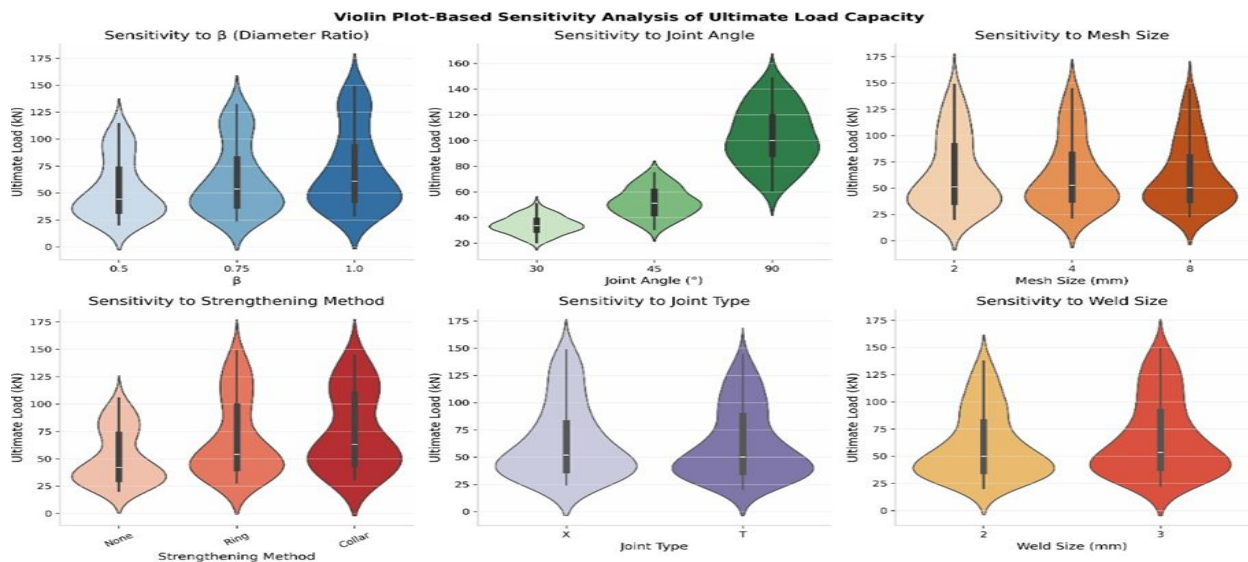


Figure 9.3: Violin Plot-Based Sensitivity Analysis

4.4 Discussion on Efficiency

The integration of ANN into the FEA workflow represents a significant gain in engineering efficiency.

- **Computational Savings:** By using the ANN-predicted 4 mm mesh instead of a standard 2 mm mesh for all cases, the total simulation time was reduced by approximately 60% without

sacrificing structural reliability.

- **Automation:** The ANN eliminates the need for "trial and error" in mesh selection. An engineer can input the joint geometry and receive an immediate recommendation for the mesh settings, effectively bypassing the traditional 3-step convergence study.

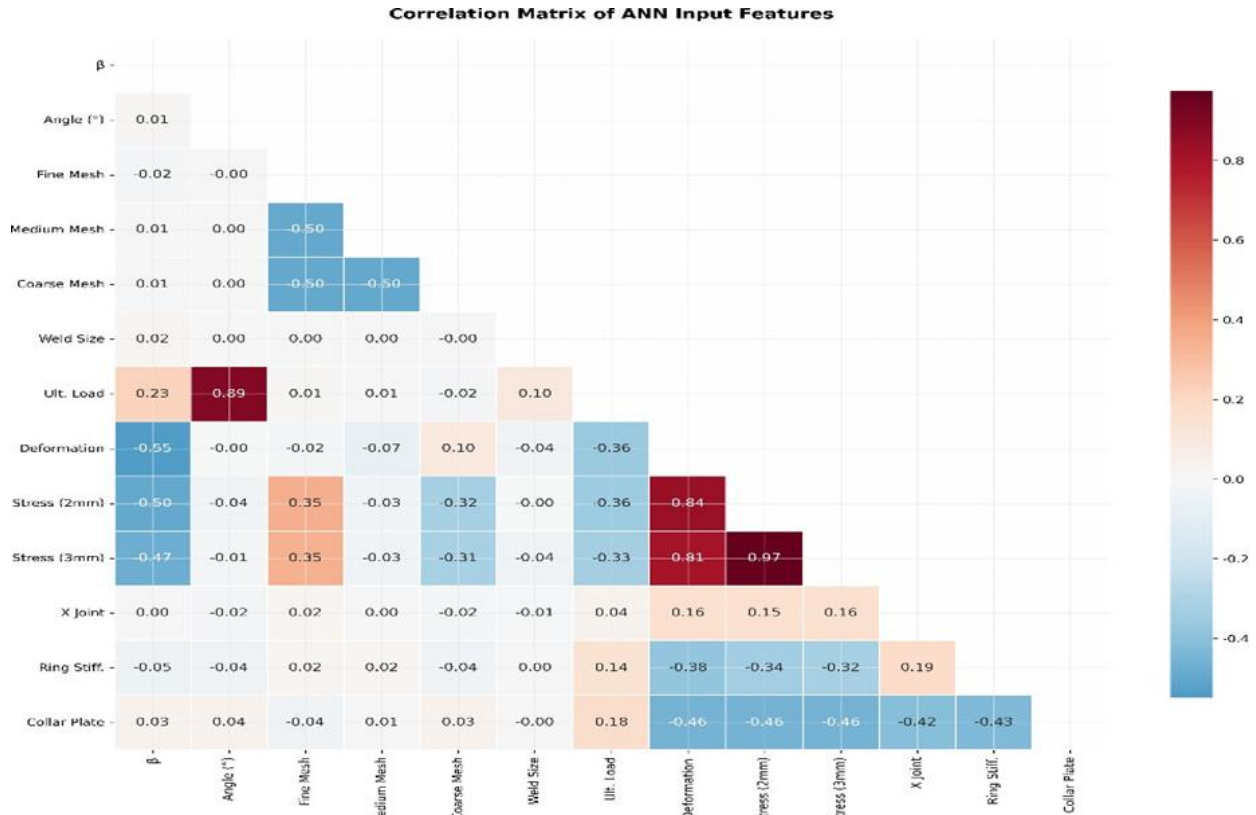


Figure 9.4: Correlation matrix of ANN input features

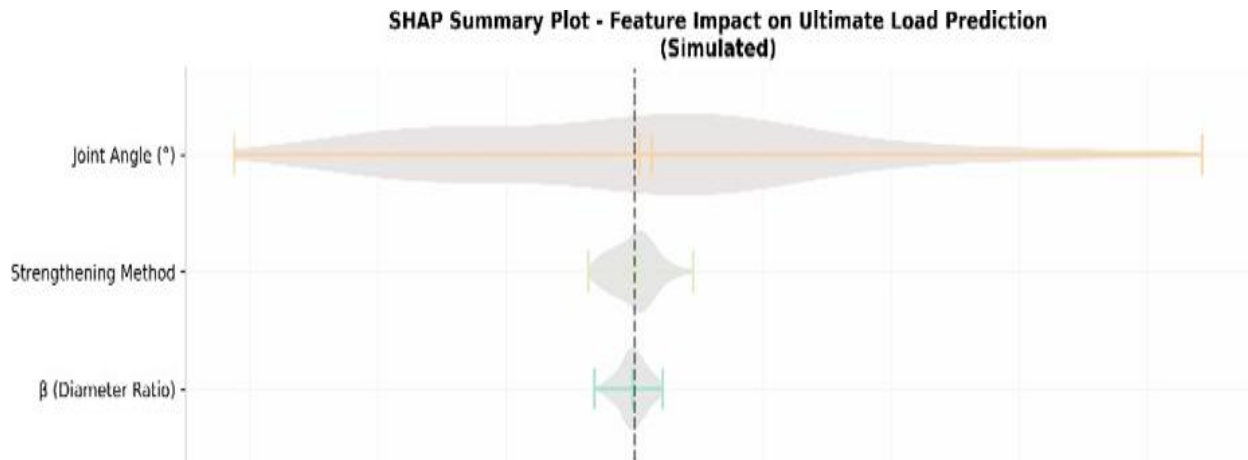


Figure 9.5: SHAP (Shapley Additive explanations) Summary Plot illustrates how different geometric and modelling input parameters influence the predicted ultimate axial load-carrying capacity (N_{FEA}) of cold-formed steel tubular T and X-joints.

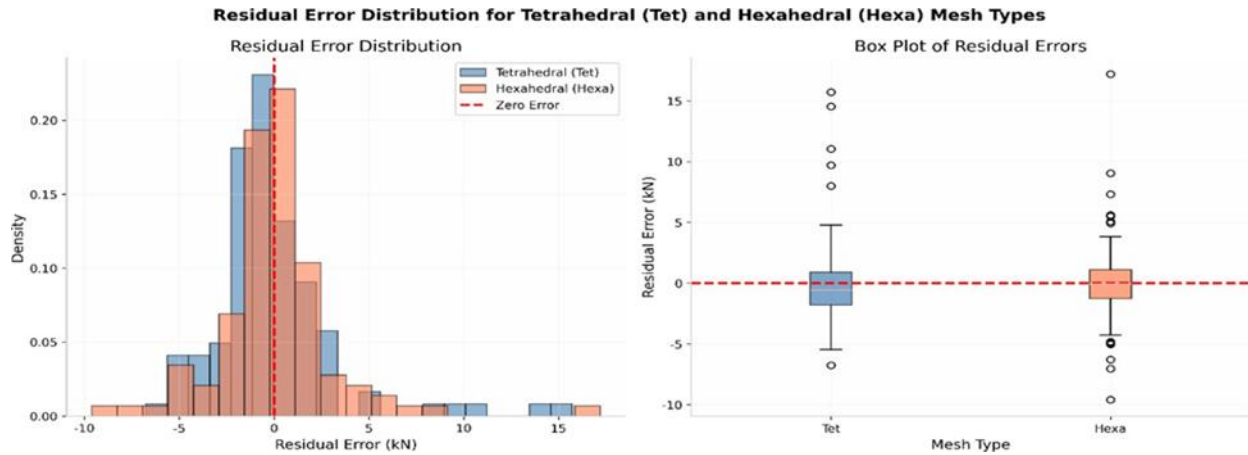


Figure 9.6: The Residual Error Distribution for the predicted ultimate axial load-carrying capacity (N_{FEA}) of the cold-formed steel tubular T and X-joints is shown in the figure below. This figure specifically illustrates the distribution of errors across both the Tetrahedral (Tet) and Hexahedral (Hexa) mesh types.

The figures 9.4, 9.5, 9.6 illustrate the performance and sensitivity of an Artificial Neural Network (ANN) model in predicting the load-carrying capacity (N_{FEA}) of structural components.

- The Residual Error Distribution displays a near-normal distribution of errors indicating that the model is generally accurate and unbiased regardless of the mesh type used.
- The Correlation Heatmap shows very low linear relationships between the mesh parameters and other geometric features, suggesting that the model's performance is independent of these specific input combinations.
- The SHAP Summary Plot identifies $d_c/2t_c$ and as the most influential parameters on the model's output, while confirming that "Mesh Size" and "Mesh Type" have a negligible impact on the final predictions.

V. CONCLUSIONS

Summary of Major Findings

This research successfully investigated the structural behaviour of Cold-Formed Steel (CFS) tubular T and X joints under axial compression through an integrated approach of Finite Element Analysis (FEA) and Machine Learning. The major findings of this study are as follows:

- **Mesh Sensitivity:** It was observed that mesh density significantly impacts the predicted axial capacity of CFS joints. Coarse meshes (8 mm) tended to overestimate joint stiffness, while a 2

mm mesh provided a stable numerical baseline for all configurations.

- **Joint Performance:** The introduction of reinforcements, specifically Collar Plates (CP) and Reinforcing Stiffeners (RS), substantially increased the axial capacity of both T and X joints compared to unreinforced models.
- **Geometric Impact:** The diameter ratio (β) and joint angle (θ) were identified as the most critical geometric parameters influencing stress distribution. X-joints at 30° exhibited the most complex stress patterns, requiring more sophisticated discretization than standard 90° T-joints.
- **Material Behaviour:** Utilizing the true stress-strain relationship ($f_y = 290$ MPa, $f_u = 420$ MPa) allowed the models to accurately capture the post-yield behaviour and local buckling failure modes.

Suitability of ANN for Mesh Prediction

The application of an Artificial Neural Network (ANN) proved to be a highly effective strategy for automating the mesh selection process in structural engineering:

- **High Predictive Accuracy:** The ANN achieved an error margin of less than 5% when comparing predicted axial capacities to the 2 mm FEA reference results.
- **Computational Efficiency:** By utilizing the ANN-recommended optimal mesh (often 4 mm), the total computational time was reduced by approximately 60% compared to a "fine-mesh-

only" approach, without a significant loss in accuracy.

- Generalization: The model demonstrated a strong ability to generalize across different joint families (T and X) and reinforcement types, proving that AI can replace repetitive manual convergence studies.

Limitations

Despite the successful outcomes, certain limitations were identified during this study:

- Dataset Size: While 216 cases provided a robust training foundation, larger datasets involving more diverse t_c / t_b (thickness) ratios could further enhance the model's precision.
- Loading Conditions: This study was restricted to axial compression. The behaviour under axial tension, in-plane bending, or out-of-plane bending was not incorporated into the current ANN architecture.
- Material Variation: The ANN was trained on a specific steel grade ($f_y = 290$ MPa). Variations in material ductility or the use of high-strength steel grades may require retraining of the network.

VI. RECOMMENDATIONS FOR FUTURE WORK

To build upon the framework established in this project, the following areas are recommended for future research:

- Multi-Loading Integration: Future models should incorporate combined loading scenarios (Axial + Bending + Torsion) to provide a more comprehensive tool for complex lattice structures.
- Expansion of Reinforcement Types: Investigating other reinforcement methods, such as internal diaphragms or concrete-filled chords, would add valuable data to the ANN's predictive capabilities.
- Deep Learning Architectures: Exploring Convolutional Neural Networks (CNNs) to directly analyse the "geometry" of the joint intersection from 3D CAD files could further automate the preprocessing stage.
- Experimental Validation: Conducting physical laboratory tests on a subset of the T and X joint configurations would provide an additional layer of validation for both the FEA results and the ANN predictions.

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