Full Paper Transactions, SMiRT 28
Toronto, Canada, August 10-15, 2025

Spatially Explicit Surrogate Models for Coupled Transmission Tower-Foundation Systems: A Graph Neural Network Framework

Mazin Mahrouqi[1], **Shayan Mazloom**[2], **Abdollah Shafieezadeh**[3], **Jieun Hur**[4], **Jae-Wook Jung**[5], **Jeong-Gon Ha**[6], **Daegi Hahm**[7]

[1] Graduate Research Associate, Risk Assessment and Management of Structural and Infrastructural Systems Laboratory (RAMSIS Lab), Department of Civil, Environmental, and Geodetic Engineering (CEGE), The Ohio State University, Columbus, OH, USA. (mahrouqi.1@osu.edu)
[2] Graduate Research Associate, RAMSIS Lab, CEGE, The Ohio State University, Columbus, OH, USA. (mazloom.1@osu.edu)
[3] Lichtenstein Professor, RAMSIS Lab, CEGE, The Ohio State University, Columbus, OH, USA. (shafieezadeh.1@osu.edu)
[4] Assistant Professor of Practice, RAMSIS Lab, CEGE, The Ohio State University, Columbus, OH, USA. (hur.55@osu.edu)
[5] Senior researcher, Advanced Structures and Seismic Safety Research Division, Korea Atomic Energy Research Institute (KAERI), Daejeon, Republic of Korea. (jaewook1987@kaeri.re.kr)
[6] Senior researcher, Advanced Structures and Seismic Safety Research Division, KAERI, Daejeon, Republic of Korea. (jgha@kaeri.re.kr)
[7] Principal researcher, Advanced Structures and Seismic Safety Research Division, KAERI, Daejeon, Republic of Korea. (dhahm@kaeri.re.kr)

ABSTRACT

Power transmission structures are vital infrastructure components whose performance during extreme weather events impacts grid reliability and the safety of nuclear power plants. Transmission system failures can lead to Loss of Offsite Power (LOOP) events at nuclear facilities, requiring activation of emergency power systems. To assess and prevent LOOP risks, finite element analysis is commonly used to simulate tower behavior under extreme loads. However, this approach is computationally intensive, especially when modeling soil-structure interaction effects, making it infeasible for comprehensive risk assessments requiring thousands of simulations. This paper presents a Graph Neural Network (GNN) framework for creating efficient surrogate models of coupled transmission tower-foundation systems. The approach represents the tower as a graph with nodes corresponding to structural joints and edges to members, preserving the physical topology. After comparing several GNN architectures, we found Graph Isomorphism Networks (GIN) with multi-fidelity transfer learning perform best. Our method leverages uncoupled simulations (500 simulations, 40,000 data points) for pre-training, followed by fine-tuning with high-fidelity coupled simulations (100 simulations, 3,000 data points), achieving high accuracy ($R^2 = 0.907$). The model captures nonlinear structural responses from initial elastic behavior through to near-failure conditions. Our transfer learning approach significantly improves spatial error distribution compared to conventional GNNs, avoiding localized error concentrations. This framework enables rapid evaluation of transmission tower performance, facilitating comprehensive resilience studies for power grids and nuclear facilities.

INTRODUCTION

Power grid failures during extreme weather events can have devastating consequences for critical infrastructure, particularly nuclear power plants. Loss of Offsite Power (LOOP) events, which occur when transmission systems fail, force nuclear facilities to rely on emergency power systems. Understanding transmission tower reliability is crucial for grid resilience and nuclear safety, especially as climate change increases the frequency of extreme weather events.

Finite Element Method (FEM) analysis has traditionally been used for evaluating transmission tower behavior under extreme loads. While FEM provides detailed structural insights, its computational cost is substantial, especially for high-fidelity simulations incorporating material and geometric nonlinearities with soil-structure interaction effects. This computational burden becomes prohibitive when conducting reliability analyses requiring thousands of simulations across varying conditions, making comprehensive risk assessments challenging.

To address these limitations, researchers have developed surrogate models that approximate FEM behavior without full physics calculations. Early approaches included response surface methods, polynomial chaos expansion, and neural networks (Forrester and Keane, 2009). While reducing computation time, these methods struggle with high-dimensional problems and cannot inherently capture structural connectivity. Graph Neural Networks (GNNs) emerged as promising alternatives that explicitly incorporate structural topology, operating directly on graph-structured data where nodes represent joints and edges represent members. Previous research has explored various GNN approaches for structural applications (Hou et al., 2024; Nourian et al., 2023; Shivaditya et al., 2022). However, significant research gaps remain, as most existing GNN models do not consider geometric or material nonlinearities essential for predicting behavior under extreme loads. Additionally, while some studies examine 3D structural systems, they typically focus on linear elastic behavior, leaving nonlinear responses near failure largely unexplored.

To address these limitations, we propose a novel GNN framework for transmission tower analysis utilizing multi-fidelity transfer learning. Our approach leverages a large dataset of computationally efficient lower-fidelity simulations to learn possible structural behaviors, then transfers this knowledge to a high-fidelity model using a smaller set of coupled tower-foundation simulations. This strategy significantly reduces computational requirements while maintaining prediction accuracy. The proposed architecture preserves structural topology while accurately predicting displacements, even under conditions approaching failure where nonlinear behavior dominates.

METHODOLOGY

This study presents a framework for creating computationally efficient surrogate models for transmission tower analysis using Graph Neural Networks (GNNs). The framework treats the tower structure as a graph, where nodes represent structural joints and edges represent beam elements. This representation enables the application of powerful graph-based deep learning techniques while preserving the structural topology.

Tower FEM Model

The transmission tower model represents a standard 138 kV electricity transmission tower with appropriate geometry and material properties. The tower consists of steel members following industry standards for yield strength and elastic modulus. Wind loads are applied to tower nodes based on design codes, reflecting realistic loading conditions during extreme weather events. The model incorporates geometric and material nonlinearities to capture structural behavior, including buckling phenomena critical to lattice tower failure modes. The tower base uses fixed boundary conditions, representing an idealized foundation. Wind load is incrementally applied until failure, characterizing the tower's load-deformation behavior from initial elastic response through collapse.

Slope and Foundation Model

The foundation system consists of concrete piles embedded in soil, with the tower situated on a sloped terrain to represent realistic field conditions. A parameterized numerical model of a single-layer homogeneous soil was created using FLAC8 to analyze the slope and foundations. The soil behavior is described by a Mohr-Coulomb material model with friction angle (ϕ), cohesion (c), and density (γ) as uncertain parameters. The slope has an inclination of 26.5 degrees and a height of 10 m. Standard displacement boundary conditions are imposed, restricting horizontal movements along the left and right edges, while both horizontal and vertical movements are fixed at the bottom boundary. To represent the pile foundations of the transmission tower, the built-in pile element model in FLAC is applied. The interactions between the piles and the soil are modeled using a spring-slider system, assuming both normal and shear equivalent stiffness to be 1.2 GPa.

Tower-Foundation Coupled FEM Model

The coupled model uses the same tower structure as the uncoupled model but replaces fixed base conditions with foundations modeled in FLAC8, as shown in Figure 1. The coupling procedure follows an iterative approach: (1) a wind load increment is applied to the tower with temporarily fixed base conditions to compute structural responses and reactions; (2) these reactions are applied to the foundation model to calculate displacements; (3) these displacements are applied to the tower base and become the new boundary conditions for the tower base; and (4) the process repeats with increasing wind loads until system failure. Each load substep requires a complete FLAC simulation, significantly increasing computational demands. This approach was verified by comparing results with an alternative method using calibrated spring elements at the tower base, with agreement between both methods confirming the coupling methodology's accuracy.

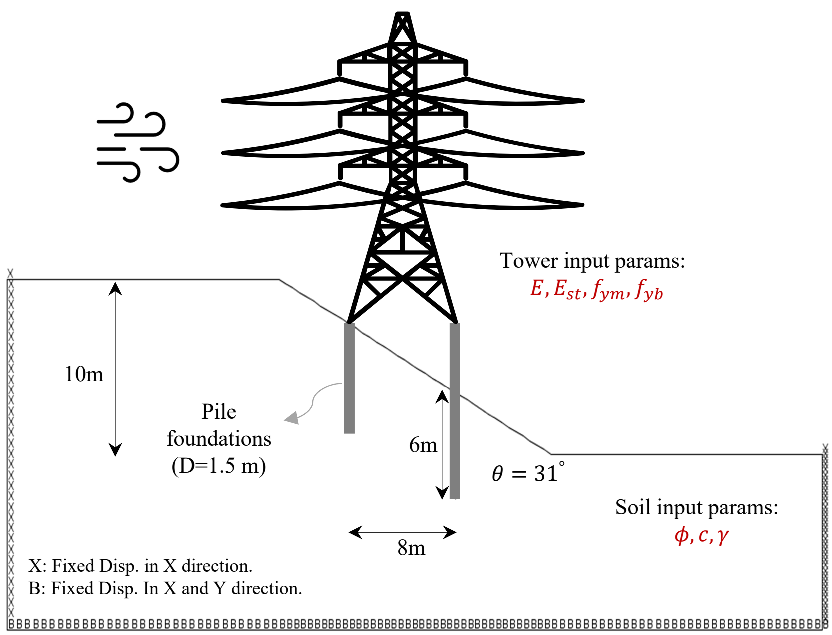

Figure 1: Schematic representation of the coupled tower-foundation system with slope. The model shows the key geometric parameters and boundary conditions, with input parameters for both the soil (c, φ, γ) and tower (E, f_{ym}, f_{yb}, E_{st}) components.

Dataset Generation

To develop robust surrogate models capable of predicting structural responses across a range of conditions, we generated extensive datasets by varying key parameters of the tower-foundation system as presented in Table 1. Both slope parameters (cohesion, friction angle, and unit weight) and steel material properties (elastic modulus, yield strengths, and post-yield elasticity) were sampled from appropriate statistical distributions to reflect realistic variability in real-world conditions. These parameters were selected based on their significant influence on the overall system behavior and potential for variation in practical applications.

Each unique combination of sampled parameters constitutes a simulation realization, with each simulation producing multiple load-deformation data points corresponding to different load levels. The number of data points per simulation varies naturally based on the convergence behavior of each specific model, with more complex nonlinear responses typically requiring smaller load increments and thus generating more data points. Following this methodology, we conducted 500 uncoupled simulations yielding approximately 40,000 data points, and 100 coupled simulations producing about 3,000 data points.

The disparity in the ratio of simulations to data points between the two models stems from the computational efficiency of adding more loading substeps in the uncoupled model compared to the coupled approach. In terms of direct computational cost, a single coupled simulation requires approximately twenty times the CPU time of an uncoupled simulation, meaning the 500 uncoupled simulations consumed only about one-quarter of the computational resources required for the 100 coupled simulations. This significant computational difference underscores the value of our transfer learning approach, which leverages the large dataset of uncoupled simulations to enhance learning from the limited but high-fidelity coupled simulations.

Table 1: Probabilistic models for uncertain parameters

Component	**Properties**	**Parameter**	**Distribution**	**Mean**	**COV**
Slope	Cohesion	c (kPa)	LogNormal	20	0.2
	Friction angle	φ (degree)	LogNormal	35	0.2
	Unit weight	γ (kN/m^3)	LogNormal	18.1	0.08
Steel material	Modulus of elasticity	E (N/m^2)	LogNormal	2.0e11	0.06
	Yield stress of main leg elements	f_{ym} (N/m^2)	LogNormal	4.02e8	0.1
	Yield stress of other elements	$f_{y\phi}$ (N/m^2)	LogNormal	2.9e8	0.1
	Post yield elasticity	E_{st} (N/m^2)	LogNormal	0.02E	0.25

GNN Framework

Our Graph Neural Network framework represents the transmission tower as a mathematical graph structure where joints in the physical structure correspond to nodes in the graph, and structural members correspond to edges as shown in Figure 2. This representation naturally preserves the tower's topology and connectivity patterns, which are crucial determinants of structural behavior. Node features incorporate all relevant information for predicting structural responses, including spatial coordinates (x, y, z) that define the geometry, applied loads (wind and gravity forces) that drive deformation, and material properties (elastic modulus, yield strength) of connected elements that govern stiffness and strength. The output of the GNN model consists of the predicted displacements $(\delta_x, \delta_y, \delta_z)$ at each node, representing the tower's deformed shape under the applied loading. This graph-based approach allows the neural network to inherently account for the interconnected nature of structural systems, where the response of any component is influenced by the behavior of connected elements.

GNN Variants and Architecture

To evaluate the effectiveness of different graph neural network architectures for structural analysis applications, we implemented and compared several established GNN variants. The Graph Convolutional Network (GCN) introduced by Kipf and Welling, 2017 provides efficient neighborhood mixing through normalized adjacency operations:

$$\mathbf{H}^{(l+1)} = \hat{\mathbf{D}}^{-\frac{1}{2}}\hat{\mathbf{A}}\hat{\mathbf{D}}^{-\frac{1}{2}}\mathbf{H}^{(l)}\mathbf{W}^{(l)},$$

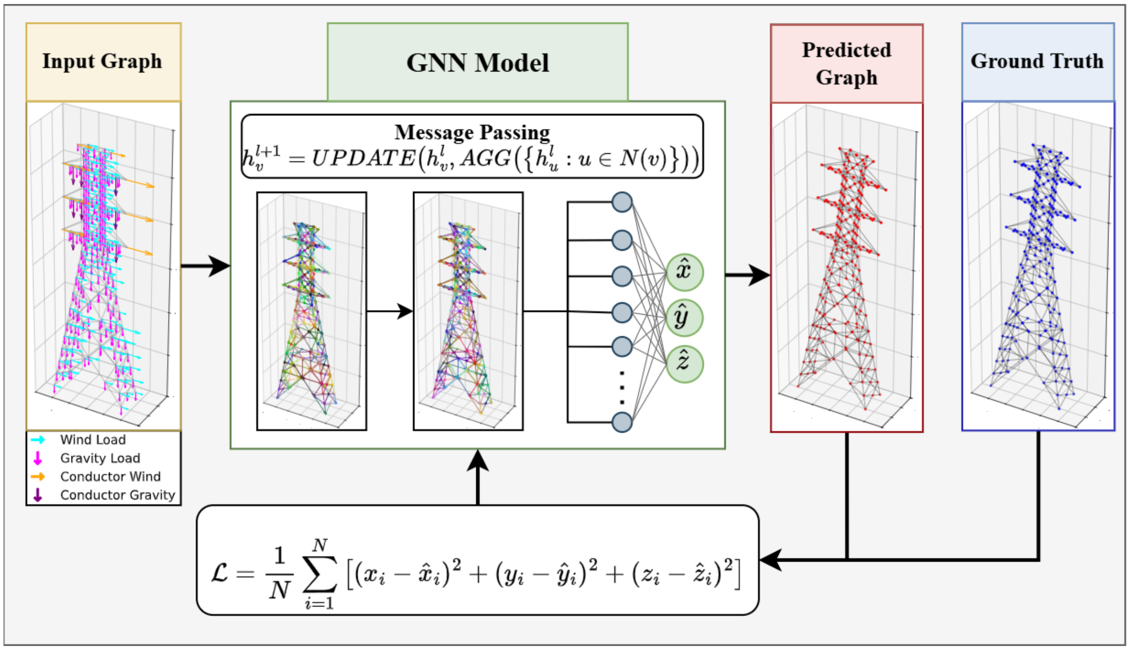

Figure 2: GNN framework applied to the transmission tower structure, showing the transformation from physical structure to graph representation and the subsequent processing through GNN layers.

where $\hat{\mathbf{A}} = \mathbf{A} + \mathbf{I}$ includes self-loops, $\hat{\mathbf{D}}$ is the corresponding degree matrix, $\mathbf{H}^{(l)}$ is the node feature matrix at layer l, and $\mathbf{W}^{(l)}$ is the weight matrix for layer l.

The GraphSAGE architecture introduced by Hamilton et al., 2017 enables efficient handling of large graphs through neighborhood sampling:

$$\mathbf{h}_v^{(l+1)} = \sigma\Big(\mathbf{W}^{(l)}\big[\mathbf{h}_v^{(l)} \,\|\, \mathrm{AGG}\big(\{\mathbf{h}_u^{(l)} : u \in \mathcal{N}(v)\}\big)\big]\Big),$$

where $\mathbf{h}_v^{(l)}$ is the feature vector of node v at layer l, $\mathcal{N}(v)$ represents the neighborhood of node v, σ is a non-linear activation function, and $\|$ denotes concatenation. Various aggregation functions (AGG) can be employed to combine neighborhood information.

The Graph Attention Network (GAT) proposed by Veličković et al., 2018 introduces attention mechanisms to dynamically weight neighbor contributions according to their relevance:

$$\mathbf{h}_v^{(l+1)} = \sigma\Big(\sum_{u \in \mathcal{N}(v)} \alpha_{vu}^{(l)}\, \mathbf{W}^{(l)} \mathbf{h}_u^{(l)}\Big),$$

with learned attention coefficients $\alpha_{vu}^{(l)}$ that determine the importance of node u's features to node v.

Finally, the Graph Isomorphism Network (GIN) introduced by Xu et al., 2019 achieves maximum discriminative power among GNNs through its unique update function:

$$\mathbf{h}_v^{(l+1)} = \mathrm{MLP}^{(l)}\Big((1 + \epsilon^{(l)})\mathbf{h}_v^{(l)} + \sum_{u \in \mathcal{N}(v)} \mathbf{h}_u^{(l)}\Big),$$

where $\epsilon^{(l)}$ is a learnable parameter and $\mathrm{MLP}^{(l)}$ is a multi-layer perceptron at layer l. The GIN architecture is particularly noteworthy because its aggregation function is provably the most expressive (injective) among common GNN variants, theoretically enabling it to distinguish between different graph structures more effectively than other architectures.

Multi-Fidelity Transfer Learning

Our transfer learning methodology addresses the computational challenges of generating sufficient high-fidelity coupled simulation data by leveraging knowledge from more abundant uncoupled simulations. The approach comprises three distinct phases. In the pre-training phase, we train the GNN models on the large dataset of uncoupled simulations (40,000 data points), allowing the model to learn the fundamental structural behavior patterns across diverse loading conditions and material properties. During this phase, the model develops an understanding of the relationships between applied loads and resulting deformations, though without accounting for soil-structure interaction effects. The weight transfer phase then preserves these learned structural patterns by initializing a new model instance with the weights from the pre-trained model. This critical step establishes a starting point that already incorporates substantial knowledge about structural behavior, rather than beginning the coupled model training from randomly initialized weights. Finally, in the fine-tuning phase, we train the model on the smaller dataset of high-fidelity coupled simulations (3,000 data points). This phase allows the model to adapt its previously learned patterns to account for the additional complexity introduced by soil-structure interaction, effectively transferring knowledge from the simpler domain to the more complex one. This transfer learning approach significantly reduces the computational burden of training accurate surrogate models for coupled tower-foundation systems while maintaining high prediction accuracy.

RESULTS AND DISCUSSION

The performance of various GNN architectures for predicting transmission tower deformation under nonlinear static pushover analysis is evaluated through multiple metrics. The results demonstrate the capabilities of these models to capture complex structural behaviors while highlighting the significant advantages of transfer learning approaches.

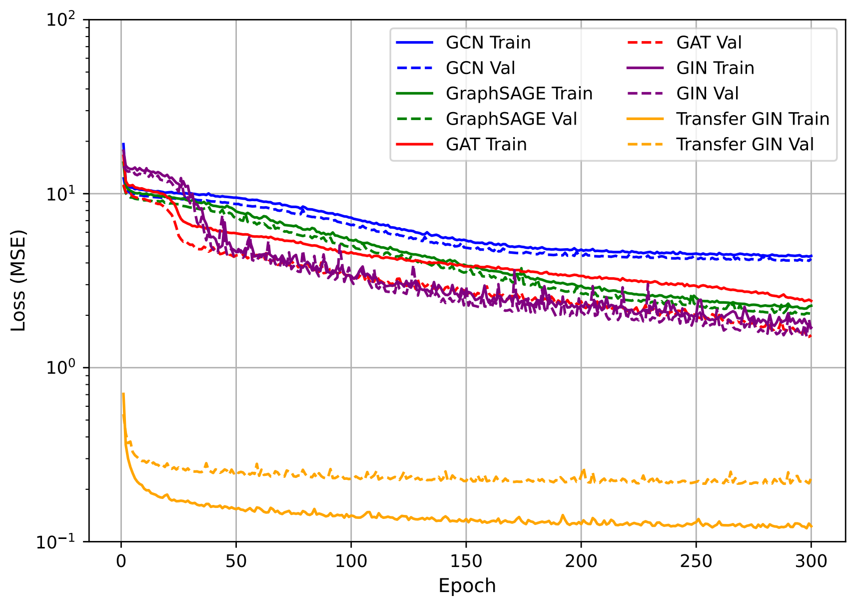

Figure 3: Loss of different GNN architectures during training, showing the evolution of MSE for both training and validation datasets. The transfer learning approach with GIN significantly outperforms the other models.

Figure 3 illustrates the training performance of different GNN architectures, plotting the evolution of MSE loss for both training and validation datasets. Among the standard training approaches, GIN demonstrates superior performance, achieving lower loss values more rapidly than GCN, GraphSAGE, and GAT. This suggests that GIN's architecture, with its maximum discriminative power through sum aggregation and MLPs, is particularly well-suited for structural analysis tasks.

Most notably, the multi-fidelity transfer learning approach with GIN exhibits significantly improved performance. By leveraging pre-training on 40,000 uncoupled low-fidelity simulation data points, before fine-tuning on 3000 coupled high-fidelity data points, the multi-fidelity transfer learning model achieves substantially lower loss values. This efficiency is particularly significant because the coupled simulations are considerably more computationally expensive due to the coupling operations occurring at every substep, highlighting the practical value of the transfer learning approach.

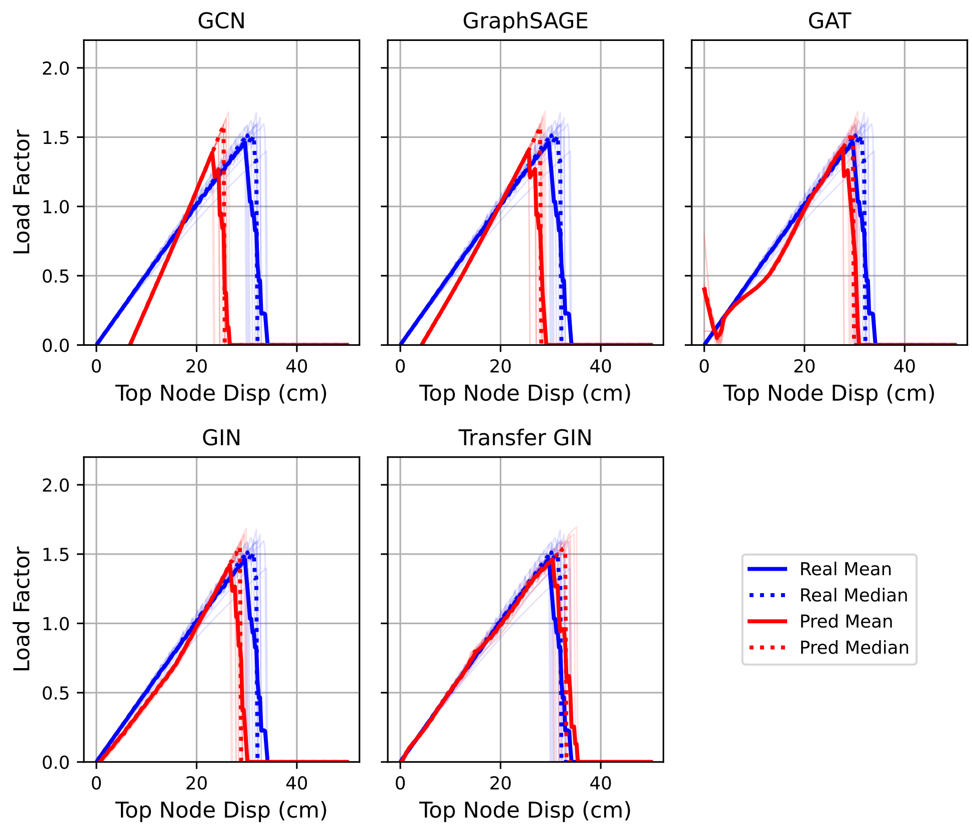

Figure 4: Comparison of load-deformation relationships predicted by different GNN models against FEM results, demonstrating the ability of the models to capture nonlinear structural behavior.

Figure 4 presents the load-deformation relationships predicted by different GNN models compared against FEM results. These plots reveal important insights that are not fully captured by training loss metrics alone. GCN and GraphSAGE models exhibit a clear bias toward predicting deformation states that are close to the average deformed state - they consistently overestimate deformations at lower loads while underestimating deformations at higher loads. While they capture the general linear aspect of the initial structural response, they fail to accurately represent the extremes of the load-displacement curve.

GAT models, despite showing competitive loss values during training, demonstrate particularly poor performance at lower load factors. As loading increases, GAT performance improves, suggesting that these models might be more effective at capturing specific high-load instances but lack the ability to generalize across the entire loading range.

Standard GIN models show markedly better performance throughout the loading range, more accurately capturing both the initial linear response and the nonlinear behavior near failure. The GIN with multi-fidelity transfer learning significantly outperforms all others, closely following the true load-displacement curve across loading conditions.

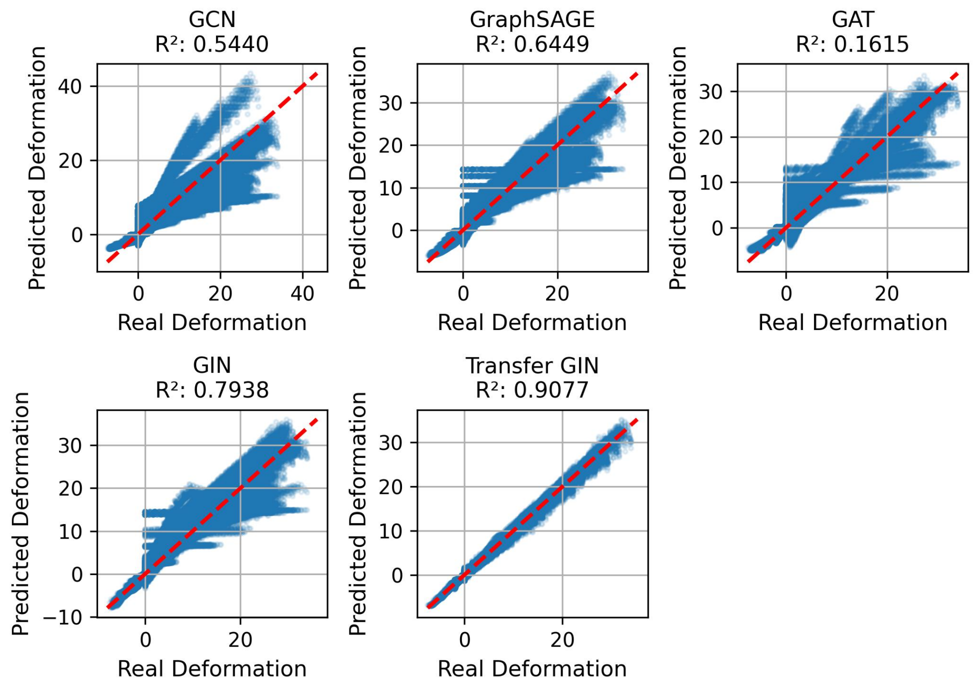

Figure 5: R^2 performance evaluation comparing actual displacements (x-axis) versus predicted displacements (y-axis) for different GNN architectures. Each point represents a single displacement component (x, y, or z) for a specific node across all test simulations and loading conditions.

The R^2 scores presented in Figure 5 provide a comprehensive evaluation of model performance across all nodes, directions, and test simulations. Despite showing competitive loss values during training, GAT models demonstrate substantially lower R^2 scores, suggesting that they may perform well in specific instances but suffer from high error variability that significantly impacts overall predictive quality.

The Transfer GIN model consistently outperforms all other architectures across different simulations and loading conditions, achieving an R^2 score of 0.907. This superior performance highlights the value of transfer learning in structural analysis applications, where high-fidelity simulations are computationally expensive but lower-fidelity models can provide valuable initial knowledge that generalizes well to the coupled system behavior.

Figure 6 visualizes the spatial distribution of prediction errors for all five models at three different loading states (10%, 50%, and 90% of failure load). This visualization provides critical insights into how errors are distributed throughout the structure and how models handle increasing nonlinearity.

A notable observation is the tendency of GCN, GraphSAGE, GAT, and GIN models to produce highly localized errors, with certain nodes exhibiting significantly larger prediction inaccuracies than others. This error localization is problematic for structural applications, as it indicates that the models may dramatically misrepresent deformations at specific locations - either severely overestimating or underestimating the actual displacements. Such localized inaccuracies could lead to incorrect assessment of structural

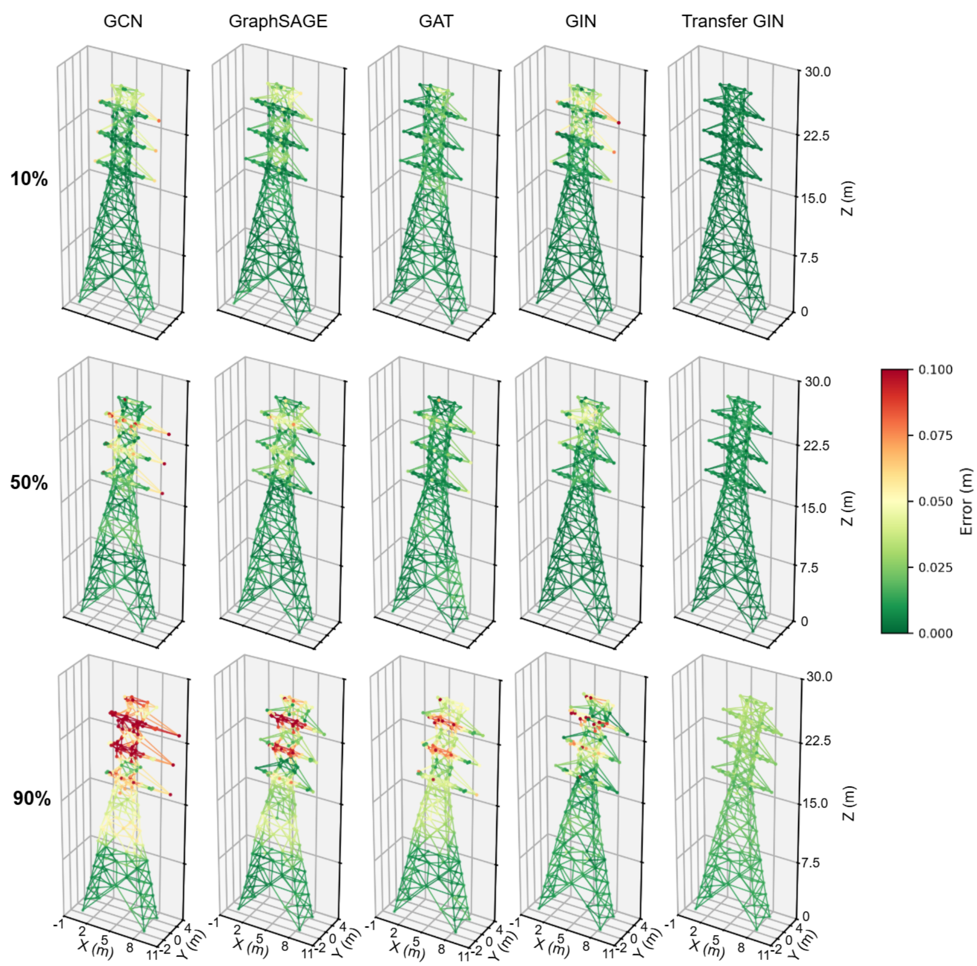

Figure 6: Visualization of predicted deformed shapes compared to FEM results, demonstrating the spatial accuracy of the GNN predictions across different loading scenarios.

integrity and potential failure mechanisms.

Interestingly, while standard GIN models show improved overall performance compared to other non-transfer approaches, they still exhibit localized error patterns. This suggests that even the more powerful GIN architecture has limitations when trained solely on the limited high-fidelity dataset.

In contrast, the transfer learning GIN model demonstrates a much smoother error distribution throughout the entire tower structure. This qualitative difference, which is not immediately apparent from other performance metrics, reveals that the transfer learning approach achieves a more global understanding of the tower's behavior. The absence of concentrated error regions indicates more robust predictions, even if errors still exist, they are distributed more evenly rather than concentrated in ways that could significantly mislead structural assessment.

CONCLUSION

This study presents a novel Graph Neural Network framework for predicting the response of coupled transmission tower-foundation systems. By leveraging multi-fidelity transfer learning, we demonstrate that knowledge from computationally efficient uncoupled simulations can be effectively transferred to more complex coupled tower-foundation models, reducing the computational burden while maintaining high prediction accuracy. The results show that the GIN architecture with transfer learning outperforms standard GNN approaches, achieving an R^2 score of 0.907 and demonstrating superior ability to capture both the global load-deformation relationship and the spatial distribution of displacements throughout the structure.

The proposed approach offers several advantages over traditional surrogate modeling techniques. First, by explicitly incorporating the structural topology as a graph, our model better captures the spatial relationships between structural components than conventional neural networks. Second, the transfer learning strategy enables accurate prediction of coupled tower-foundation behavior with far fewer high-fidelity simulations than would otherwise be required. Finally, the model's ability to predict displacements at all nodes simultaneously provides comprehensive insight into structural behavior under extreme loading conditions.

These capabilities make the proposed framework particularly valuable for infrastructure resilience studies and comprehensive risk assessments, where thousands of simulations across different loading scenarios and structural configurations are required. Future work will focus on extending this methodology to dynamic loading conditions and incorporating additional soil-structure interaction effects to further enhance the model's predictive capabilities for critical infrastructure systems.

ACKNOWLEDGMENT

This work was supported in part by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry & Energy (MOTIE) of the Republic of Korea (No. RS-2022-KP002850), the U.S. National Science Foundation under grant 2000156, as well as the Lichtenstein endowment at The Ohio State University. The authors also appreciate the support by an allocation of resources for computing time from the Ohio Supercomputer Center (OSC). Any opinions, findings, and conclusions expressed are those of the authors and do not necessarily reflect those of the sponsoring organization.

References

Forrester, A. I. J., & Keane, A. J. (2009). Recent advances in surrogate-based optimization. *Progress in Aerospace Sciences*, *45*(1), 50–79. https://doi.org/10.1016/j.paerosci.2008.11.001

Hamilton, W., Ying, Z., & Leskovec, J. (2017). Inductive Representation Learning on Large Graphs. *Advances in Neural Information Processing Systems*, *30*. Retrieved February 26, 2025, from https://proceedings.neurips.cc/paper/2017/hash/5dd9db5e033da9c6fb5ba83c7a7ebea9-Abstract.html

Hou, W., Li, Y., & Wang, C. (2024). FrameGraph: A Scalable Performance Evaluation Method for Frame Structure Designs Using Graph Neural Network. *Journal of Mechanical Design*, *146*(121703). https://doi.org/10.1115/1.4065612

Kipf, T. N., & Welling, M. (2017, February). Semi-Supervised Classification with Graph Convolutional Networks [arXiv:1609.02907 [cs]]. https://doi.org/10.48550/arXiv.1609.02907
Comment: Published as a conference paper at ICLR 2017.

Nourian, N., El-Badry, M., & Jamshidi, M. (2023). Design Optimization of Truss Structures Using a Graph Neural Network-Based Surrogate Model [Number: 8 Publisher: Multidisciplinary Digital Publishing Institute]. *Algorithms*, *16*(8), 380. https://doi.org/10.3390/a16080380

Shivaditya, M. V., Alves, J., Bugiotti, F., & Magoules, F. (2022, November). Graph Neural Network-based Surrogate Models for Finite Element Analysis [arXiv:2211.09373]. https://doi.org/10.48550/arXiv.2211.09373

Veličković, P., Cucurull, G., Casanova, A., Romero, A., Liò, P., & Bengio, Y. (2018, February). Graph Attention Networks [arXiv:1710.10903 [stat]]. https://doi.org/10.48550/arXiv.1710.10903
Comment: To appear at ICLR 2018. 12 pages, 2 figures.

Xu, K., Hu, W., Leskovec, J., & Jegelka, S. (2019, February). How Powerful are Graph Neural Networks? [arXiv:1810.00826 [cs]]. https://doi.org/10.48550/arXiv.1810.00826