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Nonlinear analysis of truss structures based on machine learning

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ABSTRACT

This study proposes a nonlinear analysis method for truss structures using deep-learned truss elements. Truss structures can fail when subjected to extreme load due to buckling. Conventional truss elements used when modeling truss structures cannot represent buckling behavior. To consider buckling, beam elements need to be used, but they require a higher degree of freedom compared to truss elements. Furthermore, the nonlinear analysis of complex structures may encounter challenges related to convergence and computational time. In this study, we propose a new nonlinear analysis method for truss elements capable of representing buckling behaviors. This approach significantly reduces the degrees of freedom required in nonlinear finite element analysis and improves the convergence and computational efficiency.

1. INTRODUCTION

The collapse of most structures, particularly slender structures like cables, bars, and thin shells, can be attributed to nonlinear behavior. When the slender structure is subjected to compressive loads, it becomes susceptible to a phenomenon called buckling. Buckling analysis is crucial for the truss structures, which are typically composed of reinforcing bars that primarily experience axial loads. To prevent such failures, it is essential to analyze the buckling behavior of truss structures accurately.

Thai (2009) conducted a study on improving the Newton-Raphson method to improve the accuracy of nonlinear analysis of truss structures. Since nonlinear analysis uses an incremental-iterative solution, it has a computationally expensive problem. Recently, research is being conducted to replace Newton-Raphson's iterative calculation procedure using neural networks and machine learning (Mai 2021). Bidmeshki (2021) used a genetic algorithm, and Ojha (2023) used a heuristic optimization algorithm to replace Newton-Raphson's iterative calculation procedure, thereby increasing the efficiency of nonlinear analysis of truss structures. However, the truss elements, which only transmit axial forces, cannot account for structural bending, making the analysis of buckling behavior difficult. Beam elements (Yoon K 2014, 2015, Kim HJ 2020, 2021) that

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can implement bending have more degrees of freedom than truss elements, and have the disadvantage of poor convergence in complex structures. Many studies have been conducted to improve the performance of finite elements using machine learning (Jeong J 2020, 2022). In the analysis of truss structure, research using deep learning is being conducted.

In this study, buckling analysis is performed by selecting a representative member (length, cross-section etc.) and applying it to a single beam with initial imperfection. The hysteresis response obtained as a result is trained through a deep learning algorithm to perform buckling analysis of truss elements.

2. PROPOSED NONLINEAR ANALYSIS METHOD OF TRUSS STURCTURE

2.1 A Data-driven truss element

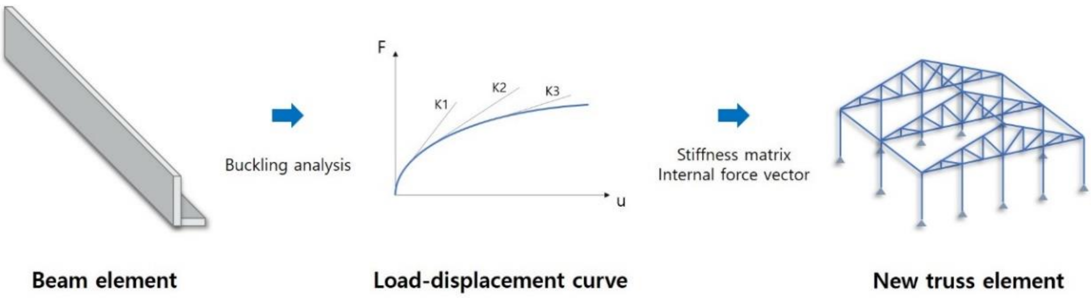

Fig. 1 Overview of a data-driven truss element

Fig. 1 is an overview of the methodology for a data-driven truss element capable of representing buckling behavior. This truss element constructs the stiffness matrix ($\mathbf{K}$) and internal force vector ($\mathbf{F}$) from the load-displacement curve obtained through the beam buckling analysis.

2.1.1 Nonlinear elastic behavior

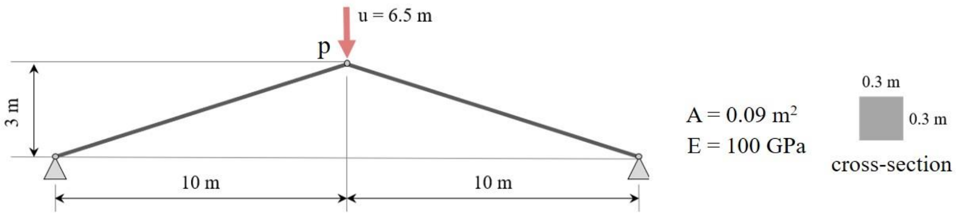

Fig. 2 Shallow 2-bar truss example

In order to check whether the proposed truss element represents buckling behavior in the elastic region, a shallow 2-bar truss example is constructed as shown in Fig. 2 and nonlinear analysis is performed. The load-displacement curve at point p is obtained.

2.1.2 Nonlinear plastic behavior

In order to check whether the proposed truss element represents buckling behavior in the plastic region, the same example as in 2.1.1 is constructed and nonlinear analysis is performed. A bilinear elastic-plastic material model is used, and the yield strength is 200.2 MPa. In plastic analysis, since the material is permanently deformed under load, the history of the load must be considered. Perform the same loading-unloading analysis as the load history received by the truss structure in 2.1.1 to obtain the hysteresis curve. By applying this to the proposed truss element, the load-displacement curve at point p was obtained, and it was confirmed that the behavior is similar to that of the beam.

2.2 Deep-learned truss element

Calculating hysteresis each time the structure of the truss changes can be computationally inefficient, especially for large and complex truss systems. Various load-displacement hysteresis datasets are generated and used for the deep learning model training.

2.2.1 Training dataset for deep-learned truss element

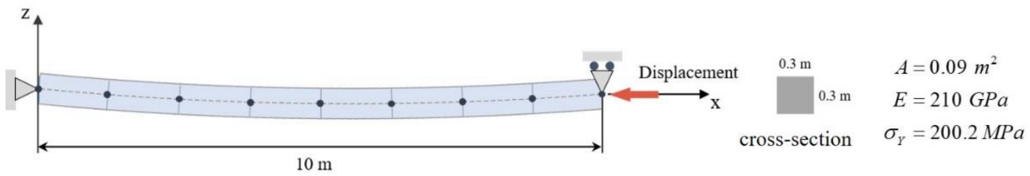

Fig. 3 Single beam with initial imperfection

To generate various load-displacement hysteresis training datasets, the Beam element of ADINA 9.8 is used. Fig.3 is a single beam with initial imperfection, and buckling analysis is performed. In order to generate various hysteresis data, irregular displacement loads are defined using the superposition of sine function.

2.2.2 Training model for deep-learned truss element

For load-displacement hysteresis training, this paper use DNN (Deep Neural Network) known as the basic model and LSTM (Long Short-Term Memory) suitable for processing sequence data. In the case of LSTM, training proceeds by predicting the next step according to the state change of the truss after the first load step by using the training method called rolling prediction and sequence update.

3. CONCLUSIONS

This study proposes a deep-learned truss element capable of representing buckling behavior. The data-driven truss element is constructed by calculating the stiffness matrix and internal force vector from the buckling analysis results of a single beam. As a result of nonlinear analysis in the elastic and plastic regions using the data-driven truss element, the feasibility that the same buckling behavior as the beam can be implemented is confirmed.

In the plastic region, a loaded member is permanently deformed, so it is essential to consider the past load history. Various load-displacement hysteresis data are generated, and the predicted value of the previous step is used as an input to predict the value of the next step using DNN and LSTM model. The deep-learned truss element that calculates the stiffness matrix and internal force vector using the LSTM model prediction value whenever the load of the truss structure changes is proposed.

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REFERENCES

Thai, H. T., & Kim, S. E. (2009). Large deflection inelastic analysis of space trusses using generalized displacement control method. Journal of Constructional Steel Research, 65(10-11), 1987-1994.

Mai, H. T., Kang, J., & Lee, J. (2021). A machine learning-based surrogate model for optimization of truss structures with geometrically nonlinear behavior. Finite Elements in Analysis and Design, 196, 103572.

Bidmeshki, S., & Habibi, A. (2021). A new procedure for post-buckling analysis of plane trusses using genetic algorithm. Steel and Composite Structures, 40(6), 817-828.

Ojha, V., Pantò, B., & Nicosia, G. (2023). Adaptive search space decomposition method for pre-and post-buckling analyses of space truss structures. Engineering Applications of Artificial Intelligence, 117, 105593.

Yoon, K., & Lee, P. S. (2014). Nonlinear performance of continuum mechanics based beam elements focusing on large twisting behaviors. Computer Methods in Applied Mechanics and Engineering, 281, 106-130.

Yoon, K., Lee, P. S., & Kim, D. N. (2015). Geometrically nonlinear finite element analysis of functionally graded 3D beams considering warping effects. Composite Structures, 132, 1231-1247.

Jung, J., Yoon, K., & Lee, P. S. (2020). Deep learned finite elements. Computer Methods in Applied Mechanics and Engineering, 372, 113401.

Jung, J., Jun, H., & Lee, P. S. (2022). Self-updated four-node finite element using deep learning. Computational Mechanics, 69(1), 23-44.

Kim, H. J., Yoon, K., & Lee, P. S. (2020). Continuum mechanics based beam elements for linear and nonlinear analyses of multi-layered composite beams with interlayer slips. Composite Structures, 235, 111740.

Kim, H. J., Lee, D. H., Yoon, K., & Lee, P. S. (2021). A multi-director continuum beam finite element for efficient analysis of multi-layer strand cables. Computers & Structures, 256, 106621.