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Keynote Paper

On the application of deep learning in the finite element method

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ABSTRACT

Incorporating emerging technologies into FEM (Finite Element Method) can lead to a leap in FEM technology. Deep learning can be applied to FEM. In this presentation, we introduce two methods of creating finite element stiffness matrices using deep learning, one of the artificial intelligence techniques. In the first method, we generate reference data models from various finite element shapes and create stiffness matrices by training strains extracted from the reference data models using deep learning. The finite elements are called deep learned finite elements (DLFE). In the second method, stiffness matrices are created by employing the assumed modal strain for bending modes and setting local coordinates using deep learning. The finite element developed improves the solution accuracy through an iterative solution procedure without mesh refinement, which we call a self-updated finite element (SUFE). The performance of the presented elements is demonstrated by various numerical examples. Through this study, we show that deep learning can be utilized for finite element development. In this presentation, deep learning is employed to improve 2D quadrilateral solid finite elements. In the future, we can extend the methods to various types of finite elements such as 3D solid, beam, and shell finite elements.

1. INTRODUCTION

FEM has been widely used to solve problems in various fields of engineering such as analyses of structural fields, heat transfer, flows and fluid-structure interactions over the past several decades (Bathe 2006). In particular, FEM is used as a powerful

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tool for structural analysis. However, the research to improve its performance is still being actively conducted.

Deep learning, an emerging technology, is increasingly being applied in various fields such as medicine, finance, and automotive industry. Deep learning has also been studied for applications in the field of numerical analysis such as computational fluid dynamics and FEM (Beck et al. 2018). Deep learning has been applied to represent FEM formulations (Takeuchi et al. 1994) and to create surrogate models (Liang et al. 2018). In this paper, two methods of calculating finite element stiffness matrices using deep learning are introduced. In the following sections, we show the concept and performance of the proposed methods.

2. PROPOSED METHODS

2.1 Deep learned finite elements (DLFE)

In the first method, we generate reference data models from various finite element shapes and create stiffness matrices by training strains extracted from the reference data models using deep learning. The finite elements are called deep learned finite elements (DLFE), which include 4- and 8-node 2D solid finite elements.

The neural network model for deep learning is considered as shown in Fig. 1, and the detailed methodology including data generation, network configuration, and training is well illustrated in Refs (Jung et al. 2020). For the efficient training of the network, we employed the normalized geometries. To consider the arbitrary geometries, pre-processing of the network input and post-processing of the network output are necessary.

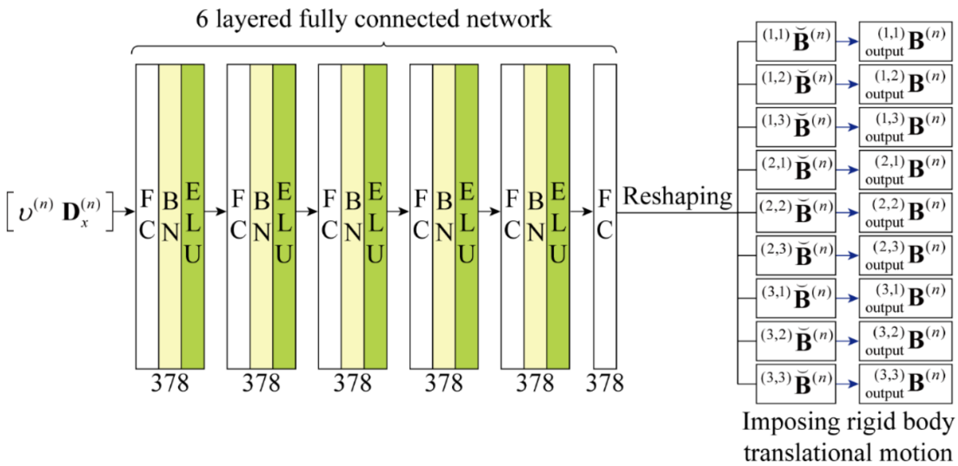

Fig. 1 Neural Network for deep learned finite elements (Jung et al. 2020)

A cook's skew beam problem is considered as shown in Fig. 2. The numerical result of the DL8 element shows good agreement with the reference solution, which is obtained using a 100×100 mesh of 9-node quadrilateral elements.

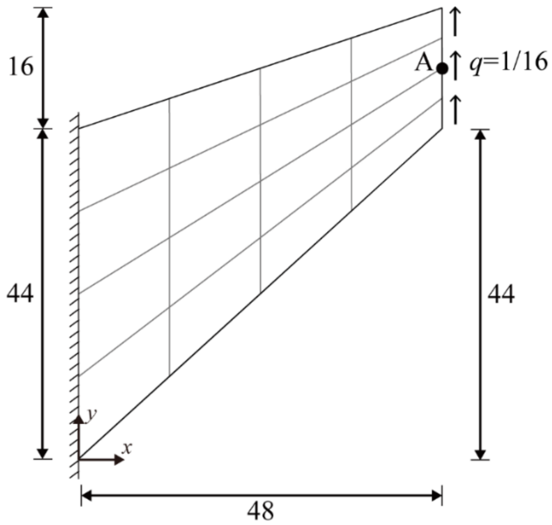

Fig. 2 Cook's skew beam problem ($E = 1.0$, $\upsilon = 1/3$, thickness $= 1.0$)

The DL8 element shows superior performance compared to the other quadratic elements through the convergence curve depicted in Fig. 3.

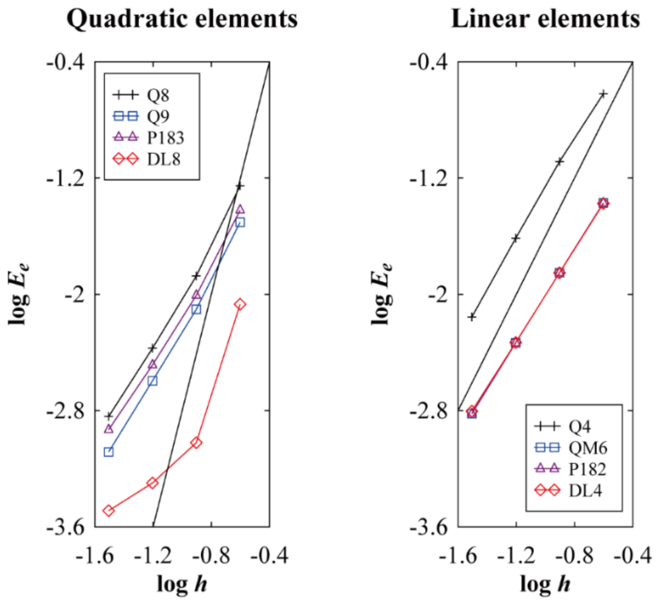

Fig. 3 Convergence curves in the Cook's skew beam problem (Jung et al. 2020)

2.2 Self-updated finite element (SUFE)

In the second method, stiffness matrices are created by employing the assumed modal strain for bending modes and setting local coordinates using deep learning. The finite element developed improves the solution accuracy through an iterative solution procedure without mesh refinement as illustrated in Fig. 4. We call the proposed element as a self-updated finite element (SUFE). The proposed method is applied to develop 4-node 2D plane stress finite element (Jung et al. 2021).

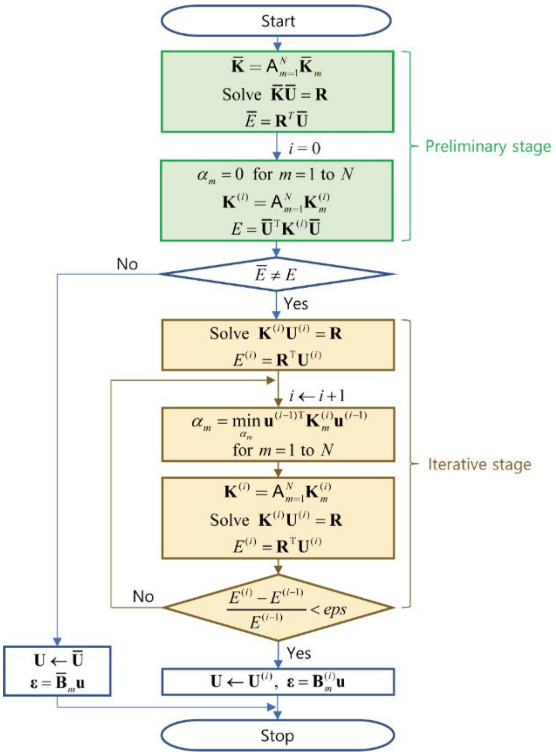

Fig 4 Iterative solution procedure for SUFE (Jung et al. 2021).

The SUFE element removes shear locking by determining the optimal bending mode to minimize the strain energy for a given displacement. This process needs iterative calculation, and solution time required to determine the bending mode is minimized using deep learning. We again consider a cook's skew beam problem. The reference solutions are given in Ref (Cook et al. 2001). The proposed SU4 element outperforms other existing 4-node elements in accuracy and convergence behavior as illustrated in Fig. 5.

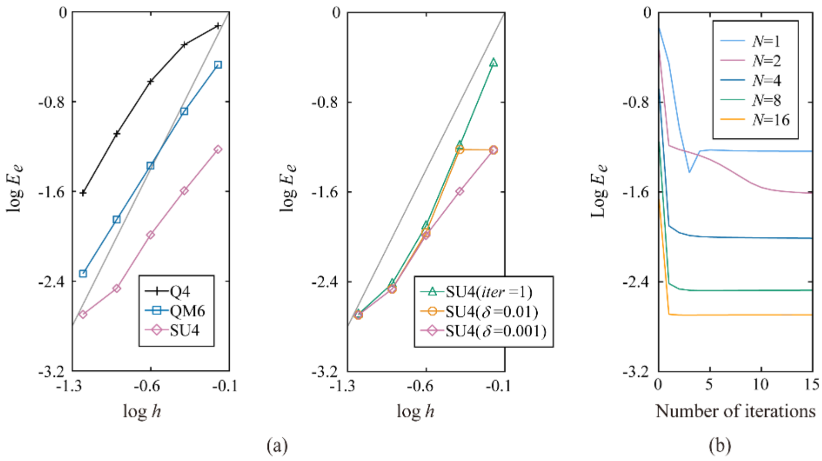

Fig 5 Performance of SUFE in the Cook's skew beam problem (Jung et al. 2021).

3. CONCLUSION

In this paper, the two methods of calculating finite element stiffness matrices using deep learning, one of the artificial intelligence techniques, were introduced. The performance of the presented elements was compared with those of other existing elements through various numerical examples. As a result, it was shown that the DLFE and SUFE have excellent accuracy and computational efficiency. From this study, we showed that deep learning can be utilized for finite element development. In this study, the presented concept is only employed to improve 2D quadrilateral solid finite elements. However, we will extend the methods to various types of finite elements such as 3D solid, beam, and shell finite elements (Ko and Lee 2017). The conduct of research on such elements in the future will be valuable.

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