

Proceedings of the Eleventh International Conference on
Engineering Computational Technology
Edited by B.H.V. Topping and P. Iványi
Civil-Comp Conferences, Volume 2, Paper 1.4
Civil-Comp Press, Edinburgh, United Kingdom, 2022, doi: 10.4203/ccc.2.1.4
©Civil-Comp Ltd, Edinburgh, UK, 2022

The potential of deep learning in the finite element method

P.S. Lee¹, S.H. Park¹ and J.H. Jung²

¹**Department of Mechanical Engineering, KAIST, Republic of Korea**

²**Korea Atomic Energy Research Institute, KAERI, Republic of Korea**

Abstract

The Finite Element Method (FEM) has been widely used to obtain reliable solutions in various engineering fields. It is necessary to promote a leap of FEM technology by incorporating emerging technologies into FEM. Deep learning, one of artificial intelligence technologies, may have the surprising potential to innovate FEM. In this presentation, we investigate potential of deep learning in FEM through our previous studies. We developed two types of finite elements called “deep learned finite elements (DLFE)” and “self-updated finite element (SUFE)”. We compare the performance of the proposed elements with those of other existing quadrilateral elements through numerical examples. The DLFE and SUFE produce improved accuracy and computational efficiency. Deep learning has the meaningful potential for finite element technology. In this study, the proposed methods were only applied to develop 2D quadrilateral solid finite elements. We will enlarge the methods to various finite elements such as triangle 2D solid, plate, and shell finite elements.

Keywords: finite element method, deep learning, 2D solid element, deep learned finite elements, self-updated finite element, shear locking, reference data model, iterative solution procedure.

1 Introduction

The Finite Element Method (FEM) has been widely used to obtain reliable solutions in various engineering fields [1]. FEM is an excellent analysis tool especially in structural engineering. However, the research efforts to improve its performance are

still being vigorously practiced. In addition, it is necessary to promote a leap of FEM technology by incorporating emerging technologies into FEM.

Deep learning, one of artificial intelligence technologies, may have the surprising potential to innovate FEM. Recently, deep learning has been widely adopted in various fields related with the 4th industrial revolution. Also, deep learning is increasingly being applied for various applications in the field of numerical analysis such as computational fluid dynamics and FEM [2]. Deep learning has been applied to represent surrogate models [3] and to construct FEM formulations [4].

In this presentation, we investigate potential of deep learning in FEM through our previous studies [5,6]. We developed two types of finite elements called “deep learned finite elements (DLFE)” and “self-updated finite element (SUFE)”. The concepts are introduced and the performance of the elements is demonstrated through some benchmark numerical examples.

Of course, it is clear that deep learning is not a one-size-fits-all solution. Nevertheless, we would like to summarize and present widely known or thought ideas about the combination of FEM and deep learning. In addition, we would like to discuss the difficulties and challenges in such study.

2 Methods

2.1. Deep learned finite elements (DLFE)

We create reference data models from random finite element shapes and produce stiffness matrices by utilizing the trained strains using deep learning illustrated in Figure 1a and Figure 1b. We call the proposed elements “deep learned finite elements (DLFE)”, which include 4- and 8-node 2D solid finite elements.

The neural network used in deep learning and the detailed methodology including data processing, training, neural network structure is illustrated in Refs [5].

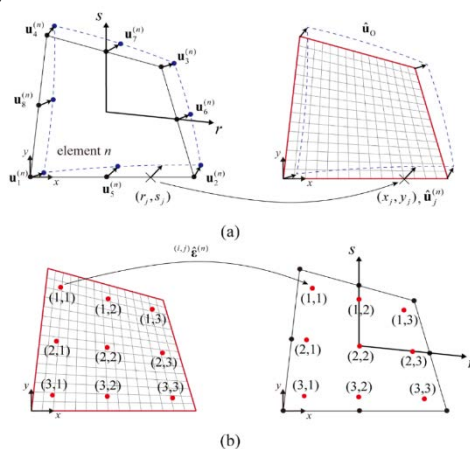


Figure 1: The reference strain data generation process (a) Random displacements creation and mapping procedure (b) Extracted strain used for deep learning. [5]

2.2. Self-updated finite element (SUFE)

We alleviate shear locking in a 4-node 2D solid element by using the assumed modal strain and setting local coordinates of bending modes using deep learning as shown in Figure 2. We call the proposed element “self-updated finite element (SUFE)”.

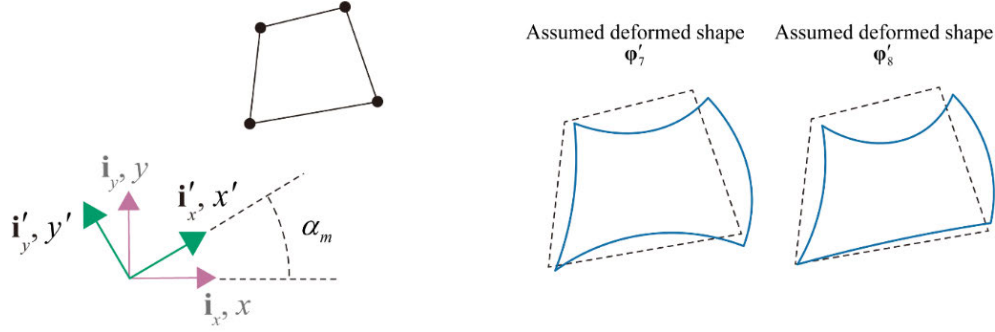


Figure 2: Assumed mode shapes of the bending modes for SUFE [6]

The proposed method significantly improves the solution accuracy through an iterative solution procedure. The procedure alleviates shear locking by setting the optimal bending axis to minimize the strain energy for a given deformation. This procedure includes iterative calculation, and the optimization time required to set the optimal bending mode is reduced using deep learning as depicted in Figure 3.

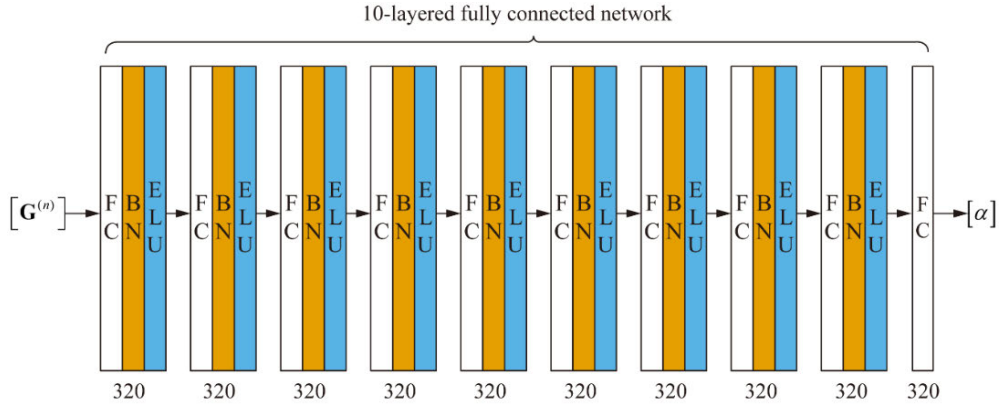


Figure 3: Neural Network used for determining the bending direction angle [6]

3 Results

3.1. Deep learned finite elements (DLFE)

We consider the tapered beam problem as shown in Figure 4. The DL8 element shows excellent performance compared to the other quadratic elements in the convergence curve represented in Figure 5. The reference solution is obtained using a fine mesh (64×64) of 9-node quadrilateral elements.

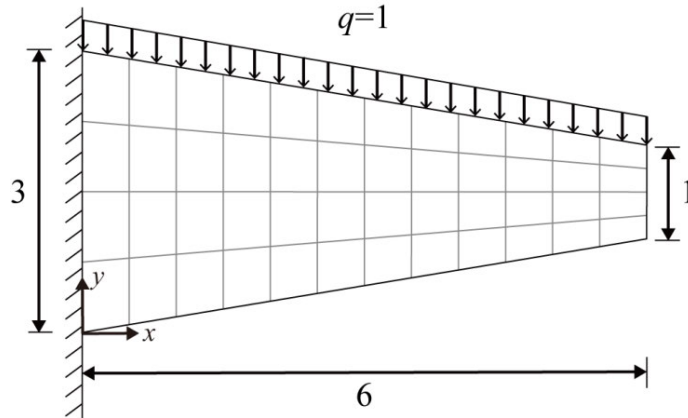


Figure 4: Tapered beam problem ($E = 3.0 \times 10^2$, $\nu = 0.3$, thickness = 0.1) [5]

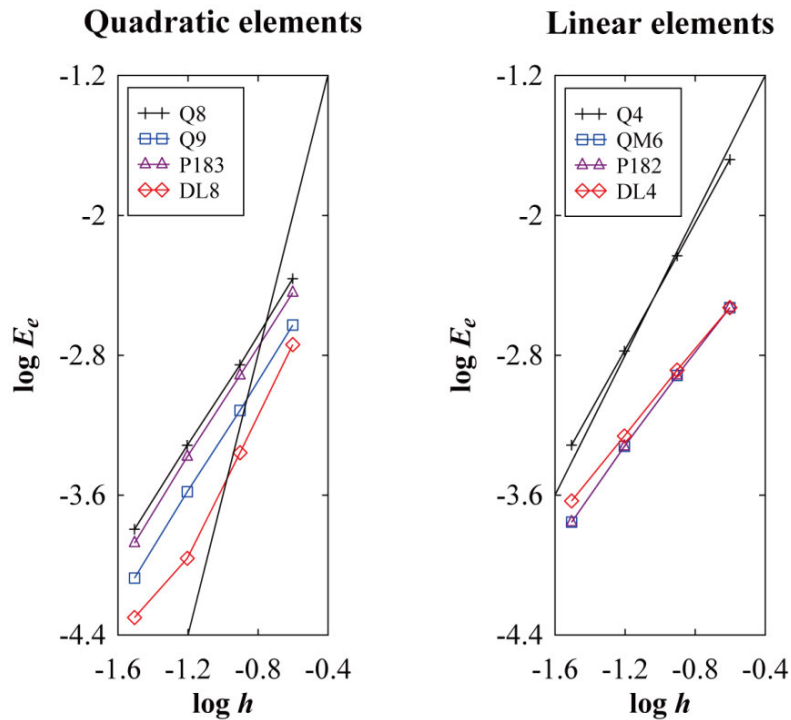


Figure 5 Performance of DLFE in the tapered beam problem [5]

3.2. Self-updated finite element (SUFE)

We consider the strap plate problem as shown in Figure 6. The reference solution is obtained using the fine mesh of standard 9-node quadrilateral elements with the number of elements, (109582 DOFs).

The SU4 element (2D 4-node solid element) shows excellent performance with a few iterations compared to the other quadrilateral elements in the convergence curve represented in Figure 7.

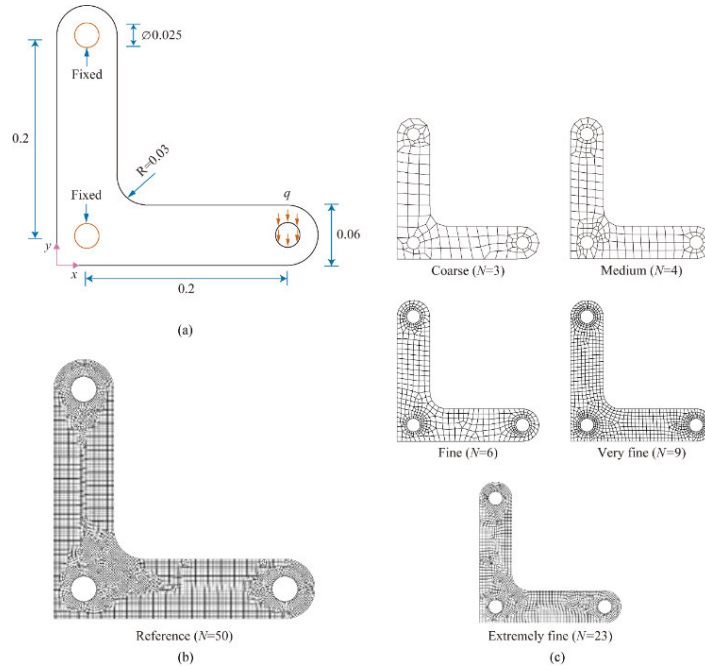


Figure 6: Strap plate problem [6]

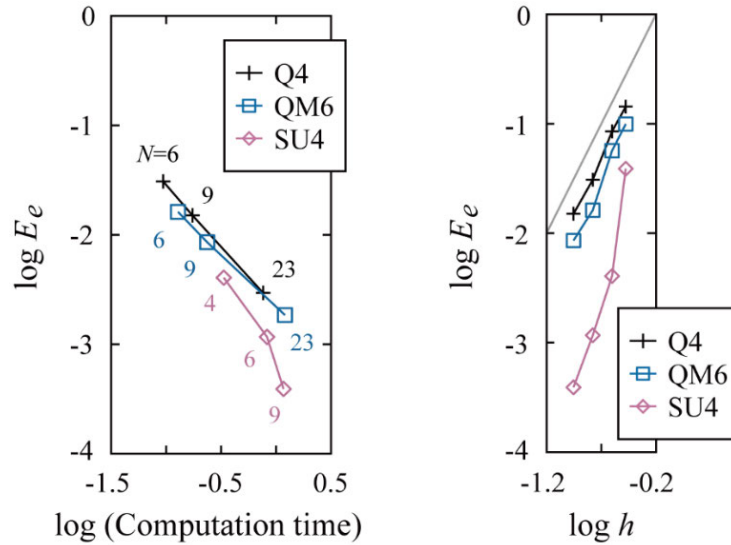


Figure 7: Performance of SUFE in the strap plate problem [6]

4 Conclusions and Contributions

We here introduced the two usages of deep learning in finite element method (DLFE and SUFE). We compare the performance of the proposed elements with those of other existing quadrilateral elements through numerical examples. The DLFE and SUFE produce improved accuracy and computational efficiency. Deep learning has the meaningful potential for finite element technology. In this study, the proposed

methods were only applied to develop 2D quadrilateral solid finite elements. We will enlarge the methods to various finite elements such as triangle 2D solid, plate, and shell finite elements [7-12].

Acknowledgements

This work was supported by “Human Resources Program in Energy Technology” of the Korea Institute of Energy Technology Evaluation and Planning (KETEP), granted financial resource from the Ministry of Trade, Industry & Energy, Republic of Korea (No. 2020403020050).

References

- [1] K.J. Bathe, “Finite element procedures”, Prentice Hall, Upper Saddle River, NJ, 2006.
- [2] A.D. Beck., D.G. Flad. and C.-D. Munz, “Deep neural networks for data-driven turbulence models”, arXiv Preprint, arXiv:1806.04482, 2018.
- [3] L. Liang., M. Liu, C. Martin, W. Sun, “A deep learning approach to estimate stress distribution: a fast and accurate surrogate of finite-element analysis”, J. R. Soc. Interface 15, 20170844, 2018.
- [4] J. Takeuchi., Y. Kosugi, “Neural network representation of finite element method”, Neural Netw. 7, 389–395, 1994.
- [5] Jung, J., Yoon, K. and Lee, PS, “Deep learned finite elements”, Comput. Methods Appl. Mech. Engrg. Volume 372, 113401, 2020.
- [6] Jung, J., Jung, H. and Lee, PS, “Self-updated four-node finite element using deep learning”, Comput. Mech. 69, 23-44, 2022.
- [7] Ko Y, Lee PS and Bathe KJ, “A new 4-node MITC element for analysis of two-dimensional solids and its formulation in a shell element”, Comput Struct 192: 34-49, 2017.
- [8] Kim S, Lee PS, “A new enriched 4-node 2D solid finite element free from the linear dependence problem”, Comput Struct 202: 25-43, 2018.
- [9] Ko Y and Lee PS, “A 6-node triangular solid-shell element for linear and nonlinear analysis”, Int J Numer Methods Eng 111: 1203-1230, 2017.
- [10] Yoon K, Lee Y, Lee PS, “A continuum mechanics based 3-D beam finite element with warping displacements and its modeling capabilities”, Struct Eng Mech 43:411–37, 2012.
- [11] Yoon K, Lee PS, “Modeling the warping displacements for discontinuously varying arbitrary cross-section beams”, Comput Struct 131:56–69, 2014.
- [12] Yoon K, Lee PS, “Nonlinear performance of continuum mechanics based beam elements focusing on large twisting behaviors”, Comput Methods Appl Mech Engrg 281:106-130, 2014.