Intelligent finite element method

A.A. Javadi*, T.P. Tan, A.S.I. Elkassas

University of Exeter, Department of Engineering, Exeter, EX4 4QF, UK

Abstract

In this paper, a neural network-based (intelligent) finite element method is presented for the analysis of civil engineering problems. The methodology is based on the integration of a neural network in a finite element (FE) framework. In the proposed methodology, a neural network is used as a substitute to the conventional constitutive material models. The efficiency of the developed methodology is illustrated by application to the analysis of a civil engineering problem.

Keywords: Finite element method; Artificial neural network; Constitutive modeling

1. Introduction

Finite element methods have, in recent years, begun to be widely used as an extremely powerful tool in analysis of geotechnical engineering problems. In this numerical analysis, the behavior of the actual material is approximated with that of an idealized material that deforms in accordance with some constitutive relationships. Therefore, the choice of an appropriate constitutive model, which adequately describes the behavior of the material, plays a significant role in the accuracy and reliability of the numerical predictions. During the past few decades, several constitutive models have been developed for various materials. Most of these models involve determination of material parameters, many of which have no physical meaning [1,2].

In this paper a neural network-based finite element (FE) analysis is presented for modeling engineering problems. The methodology involves incorporation of neural network in a finite element procedure as a substitute to conventional constitutive material models. Capabilities of the presented methodology are illustrated by application to a practical geotechnical engineering problem. The results of the analyses are compared to those obtained from conventional constitutive models. The results show that artificial neural network can be an efficient alternative to the complex mathematical constitutive models for soils in finite element analysis.

* Corresponding author. Tel.: +44 1392 263640; Fax: +44 1392 217965; E-mail: a.a.javadi@ex.ac.uk

Computational Fluid and Solid Mechanics 2005
K.J. Bathe (Editor)

2. Intelligent finite element method

2.1 Finite element method

Finite element method has been used as an efficient tool in many fields of engineering over the past 30 years. However, it is only recently that it has begun to be widely used in geotechnical engineering problems. This is probably because there are many complex issues that are specific to geotechnical engineering. One of the most crucial steps in finite element analysis is to construct constitutive models which would represent the mechanical response of the materials. Several constitutive models have been developed during the past few decades for various materials in the context of elasticity, plasticity, viscoelasticity, etc. Most of these models involve determination of material parameters, many of which have no physical meaning. In spite of considerable complexities of constitutive theories, due to the erratic nature of soils none of the existing soil models can completely describe the real behavior of various types of soil under various stress paths and loading conditions.

2.2 Neural network

A neural network is an information processing technique based on the way biological nervous systems, such as the brain, process information. Neural networks are composed of a large number of highly interconnected processing elements, or neurons, arranged generally in two or more layers. These layers include an input layer, a number of hidden layers and an output layer. Neurons in hidden layers are used to find associations within the input data and extract patterns than can provide meaningful outputs.

Back-propagation is the most widely used neural network paradigm. Each layer is composed of several neurons and these are fully connected to neurons of the succeeding layer. In this study, a three-layer back-propagation neural network was set up and trained to establish the relationship between stresses and strains from a number of triaxial tests results. The trained network was then incorporated in a FE procedure.

2.3 Intelligent finite element method

An intelligent finite element method (FEM) has been developed based on the integration of a back propagation neural network (BPNN) in a finite element framework [3,4,5,6]. In the developed methodology, the neural network is used as a substitutive to the conventional constitutive material models. A neural network is trained using the raw experimental (or in situ) data representing the mechanical response of the material to applied load. The trained network is then used in the finite element procedure to predict the constitutive relationships for the material. An intelligent FE code can be used for solving boundary value problems in the same way as a conventional FE.

3. Numerical example

The example is a tunnel subjected to gravity loading. The geometry of the tunnel and the finite element mesh are shown in Fig. 1. The finite element mesh includes 96 eight-node isoparametric elements and 336 nodes. The depth of the tunnel crown from the ground surface is 12 m. A set of laboratory triaxial test data was used in this example adopting an incremental stress–strain strategy in training the neural network.

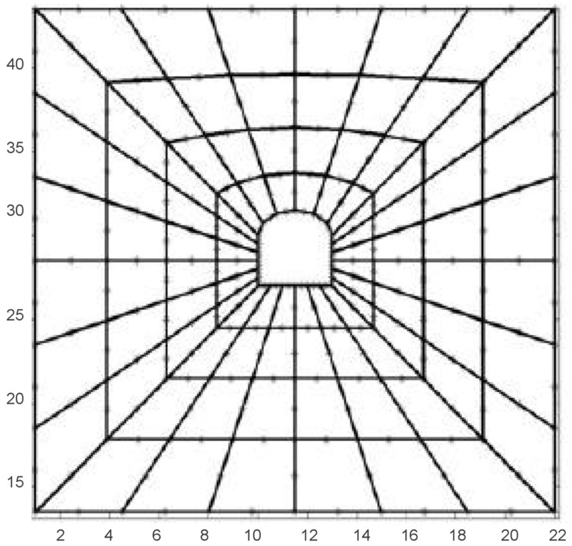

Fig. 1. Geometry of the tunnel and the FE mesh.

Figure 2a shows the results of the training process of the neural network. It is seen that, in each of these cases, the training algorithm has produced convergence between the measured triaxial test data (target values) and the artificial neural network (ANN) output. Figure 2b shows the generalization capabilities of the trained neural network. The data from the test conducted at the confining pressure of 250 kPa (which did not form a part of the training data) was used to test the trained neural network. The predicted output values of the trained neural network are compared with the experimentally

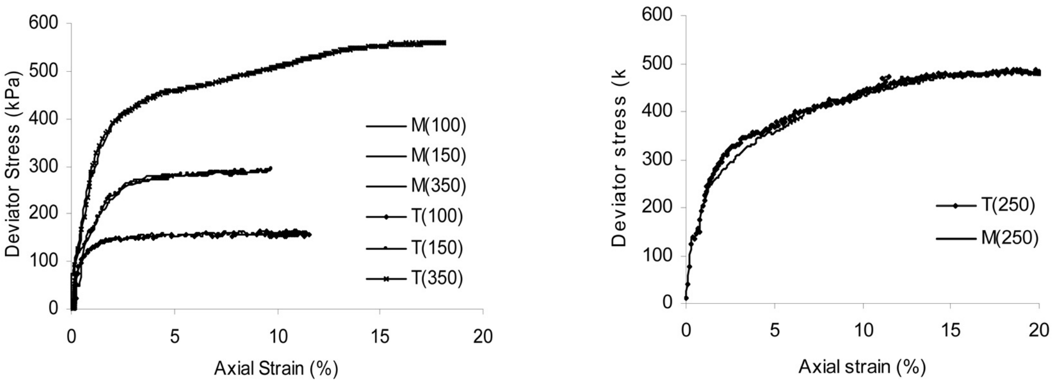

Fig. 2. (a) Results of training of the neural network, (b) stress–strain relationship predicted by the trained neural network (M = measured, T = predicted by neural network, the numbers in the brackets show the confining pressures in kPa).

Table 1
Material parameters for Duncan–Chang and Mohr–Coulomb models

c' (kPa)	ϕ' (degrees)	R_f	K	n	v	$\gamma(kN/m^3)$
20	30	0.8121	159.44	0.6233	0.33	17

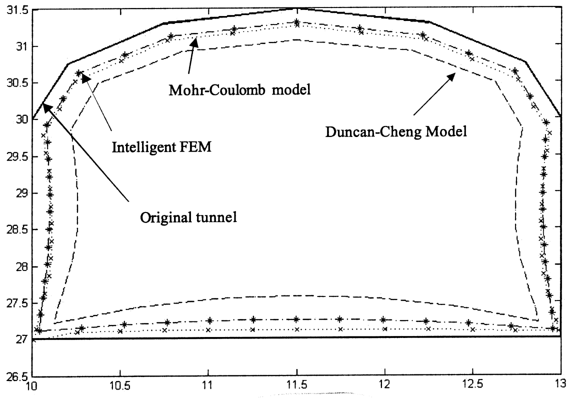

Fig. 3. Comparison of the results of the intelligent FE and conventional FE analyses.

determined values in Fig. 2b. It is seen that the generalization capability of the trained neural network is excellent. The intelligent FE code incorporating the trained neural network was used to simulate the tunnel under the gravity loading. For the conventional finite element analysis, the results of the triaxial tests were used to derive the material parameters for the Mohr–Coulomb and Duncan–Chang [7] models for the soil (see Table 1).

Figure 3 shows the comparison between the displacements in the tunnel predicted using standard FE analyses using the Duncan–Chang nonlinear elastic and Mohr–Coulomb elasto-plastic models as well as the intelligent finite element method where the raw data from the triaxial tests were directly used in deriving the neural network-based constitutive model. The patterns of deformation are similar in all three analyses. FE analysis using the Duncan–Chang model seems to have predicted greater displacements in the tunnel whereas the results of the intelligent FE analysis and the Mohr–Coulomb model are very close. Despite the relatively small difference between the results from the three different analyses, the intelligent FE results are more reliable, as this method used the original raw data to extract the constitutive relationships for the material and it did not assume a priori any particular constitutive relationships, yield conditions, etc.

From the results obtained, it is shown that the developed intelligent finite element method is capable of capturing the complex constitutive relationships of material and can offer very realistic prediction of the behavior of structures.

3. Conclusion

An intelligent finite element method has been developed based on the integration of an ANN in a FE procedure. In the developed methodology, the ANN is used as a substitute for the conventional constitutive models for the material. The efficiency and adaptability of the intelligent finite element are demonstrated by successful application to a civil engineering problem. The results of the analysis have been compared with those obtained from conventional FE analysis using conventional soil models. The results show that ANN can be successfully implemented in finite element software as an effective substitute for complicated conventional mathematical constitutive relationships. As compared with the traditional constitutive models, the ANN model has the following advantages:

The model is only based on experimental data. It is more objective than subjective, since no assumptions are made. In other words, the ANN model is not influenced by the shape of stress–strain curve. Another advantage of ANN is that as more experimental data become available, the ANN model will be able to store and train from more comprehensive information associated with the material behavior and, therefore, the ANN model will become more effective and robust.

The main benefits of using a neural network approach are that all aspects of material behavior can be implemented within a unified environment of a neural network; there is no need for complicated mathematical relationships; there are no material parameters to be identified and the network is trained directly from experimental data. The neural network is capable of capturing the main features of the material behavior while it is trained by the experimental data.

References

[1] Javadi AA, Tan TP, Zhang M. Neural network for constitutive modelling in finite element analysis. Journal of

Computer Assisted Mechanics and Engineering Sciences 2003;(10):375–381.

[2] Shin HS, Pande GN. On self-learning finite element codes based on response of structures. Computers and Geotechnics 2000;27:161–171.

[3] Javadi AA, Tan TP, Zhang M. An intelligent finite element method for analysis and geotechnical engineering applications. Proc of the 2nd MIT Conference on Computational Fluid and solid Mechanics, USA, 2003; 347–350.

[4] Javadi AA, Tan TP, Zhang M. Neural network for constitutive modeling in finite element analysis. Computer Assisted Mechanics & Engineering Sciences 2003;(10):523–529.

[5] Javadi AA, Tan TP, Elkassas ASI, Zhang M. Intelligent finite element method: development of the algorithm, Proc 6th World Congress on Computational Mechanics 2004, Beijing, China, Tsinghua; University Press and Springer-Verlag.

[6] Javadi AA, Tan TP, Elkassas ASI, Zhang M. Intelligent finite element method: geotechnical applications. Proc 6th World Congress on Computational Mechanics 2004, Beijing, China, Tsinghua; University Press and Springer-Verlag.

[7] Duncan JM, Chang CY. Nonlinear analysis of stress and strain in soils. ASCE Journal of Soil Mechanics and Foundations Division 1970;SM5:1629–1653.