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Artificial Neural Network in Approximation of Solution for Short-Cylinder-Shaped Inclusion Problem

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Abstract: Mechanical fields like strains, stresses or displacements inside isotropic infinite body with ellipsoidal-like inclusions, can be obtained easily by analytical solution given by J. D. Eshelby in 1957. Unfortunately for inclusions in form of short cylinders (e.g. steel fibers in steel-fiber-reinforced concrete) is Eshelby's solution not applicable and finite element analysis is quite time consuming. By means of artificial neural network trained on sufficiently large set of reference solutions to predict desired mechanical fields one can achieve considerable speedup at the cost of approximate solution.

Introduction

The main aim of this paper is to present our preliminary work which will allow us better understanding of materials behavior. We will apply the proposed approach to obtain mechanical response of materials consisting of short-cylinder-shaped inclusions and isotropic matrix.

In 1957 J. D. Eshelby [1] presented in his fundamental work an analytical solution for isotropic ellipsoidal inclusion. Solution can be found for any ellipsoid with arbitrary sizes of three semi-axes, even for ellipsoid with one semi-axis set to infinity which gives us an infinite cylinder. However for inclusions with shape of short cylinders the Eshelby's solution is not applicable. One of possible options is the use of finite element method (FEM), but it could be quite time consuming depending on fineness of the element mesh.

Artificial neural network

Therefore, we propose to use FEM to obtain a set of reference solutions which will be used to train an artificial neural network (ANN) [2, 3] for predicting of material response.

ANNs are computational models based on central nervous systems, especially on brain. These models are capable of machine learning and recognizing of patterns in given data. ANN consists of many simple processing nodes – so called neurons – interconnected into systems that can change their structure during the training (learning) phase. An adaptive value representing synaptic weight is assigned to each connection between two neurons. Based on given data and respective results used as an external information flowing through the system, these weights are balanced in a way that the output of ANN corresponds to the actual results. For our purposes we will use software called RegNeN [4] with implemented most widely used type of ANN called multi-layer perceptron with the sigmoid transfer function and so called backpropagation learning algorithm.

Reference solutions

First step in the whole process is creating a sufficiently large set of FEM solutions for inclusions depending on varying dimensions, material properties and load. In order to create these variable inputs in a way that the resulting set of reference solutions will evenly cover the space of possible input combinations we will generate them through software called SPERM [5] which utilizes the method of Latin Hypercube Sampling (LHS). One simulation is performed by FEM software called OOFEM [6] for each generated sample and then used for the ANN training phase.

Creating of ANN and results prediction

During the training process the actual architecture of neurons is created. Number of neurons in the input layer is equal to the number of variables in samples. Next layer - so called hidden - consists of *n* neurons, where *n* is determined automatically within the training process by testing the over-training of ANN based on the cross-validation error. The number of neurons in the last layer is equal to the number of results. To predict results for desired inclusion the parameters of relevant inclusion should be used as ANN inputs and after the simple evaluation the results are obtained.

Summary

Because the accuracy of results predicted by ANN depends on the training phase [7], creating a set of reference solutions, that provides sufficient quantity and variety of samples, is one of the essential steps in this approach. Nevertheless, certain error will always be part of the predicted results since we obtain only an approximate solution. But if the error is adequately small and we can afford to neglect it, the results are predicted many times faster than with standard FEM calculation and in case of large amounts of desired results it is possible to achieve considerable speedup.

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