Self-learning finite element method and engineering applications

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Abstract

This paper presents the development of an automation process for the self-learning finite element method (FEM) and its application to a number of engineering problems. The self-learning FEM involves the integration of a suitably trained Evolutionary Polynomial Regression (EPR) model that represents the material constitutive behaviour in the framework of the finite element method. The automation algorithm was coded in Matlab environment using a new bespoke version of EPR. Two numerical examples are presented to illustrate the proposed methodology. The results show that using EPR in the self-learning finite element method provides very accurate predictions, simplifies the training of EPR and reduces the time required for analysis.

1 –Introduction

The self-learning simulation is an extension of the autoprogressive algorithm originally introduced by Ghaboussi et al. [1]. Hashash et al. [2] proposed a self-learning simulation methodology, also called inverse analysis technique. This methodology employs the auto-progressive algorithm that extracts material's constitutive behaviour (stress-strain relationship) using global load-displacement measurements. The self-learning finite element method introduced by Hashash [2] utilizes a neural network (ANN) based constitutive model to extract the materials behaviour [2]. Although there has been valuable research on the self-learning FEM using ANN, and demonstration of the advantages that ANN offers in constitutive modelling, however, it is also known that ANNs also suffer from a number of drawbacks. For example, the number of neurons, number of hidden layers, transfer function, etc. must be determined a priori, requiring a time-consuming trial and error procedure [3]. Faramarzi et al. [4] proposed an algorithm for training EPR models and their incorporation in the self-learning procedure and highlighted the advantages of EPR over ANN. In this paper the process of EPR based self-learning FEM has been applied to overcome the problems with the ANN approach and improve the way of EPR training.

2 – Evolutionary polynomial regression (EPR)

In recent years, by rapid developments in computational software and hardware alternative computer aided pattern recognition approaches have been extended beyond classical plasticity theories to modelling many engineering problems. Evolutionary polynomial regression (EPR) is a new hybrid technique based on evolutionary computing, aimed to search for polynomial structures representing the behaviour of a system [4]. EPR is a combination of genetic algorithm (GA) which searches for symbolic structures and least square (LS) regression which is used to estimate the constants values [5]. A typical formulation of EPR expression can be stated as:

$$y = \sum_{j=1}^{m} F(\mathbf{X}, f(\mathbf{X}), a_j) + a_0 \tag{1}$$

where y is the estimated output of the system; a_j is a constant value; F is a function constructed by the process; $\mathbf{X}$ is the matrix of input variables; f is a function defined by the user; and m is the number of terms of the expression excluding bias a_0.

3 – EPR based self-learning finite element method

The methodology of incorporating an EPR in finite element analysis was first presented by Javadi and Rezania [3]. They showed that a properly trained EPR on experimental data can be implemented in a finite element model with more simplicity compared with a conventional constitutive model [3]. However, this approach of training EPR needs a large number of experiments which is costly and may not be available in all cases. Therefore, training EPR within the self-learning FEM seems to be much more efficient. The framework of the self-learning FEM consists of two steps. In step 1, the applied load and constrained boundary conditions are implemented and the boundary forces and displacements are measured for each loading increment. Two finite elements analyses are considered in parallel (FEA and FEB) and an EPR model which represents the stress-strain relationship is trained. The FE model (A) simulates a structure and applies the forces while in parallel, the FE model (B) applies the corresponding displacements. The stresses and strains are determined at each integration point for both FE models. The methodology assumes that the stresses of FE (A) are accurate and strains of FE (B) are accurate and they are used to train the EPR model. Each cycle of self-learning that accomplishes the entire applied load is called a pass. Several passes may be required to complete the analysis. The flowchart of the EPR-based self-learning FEM is shown in Figure 1.

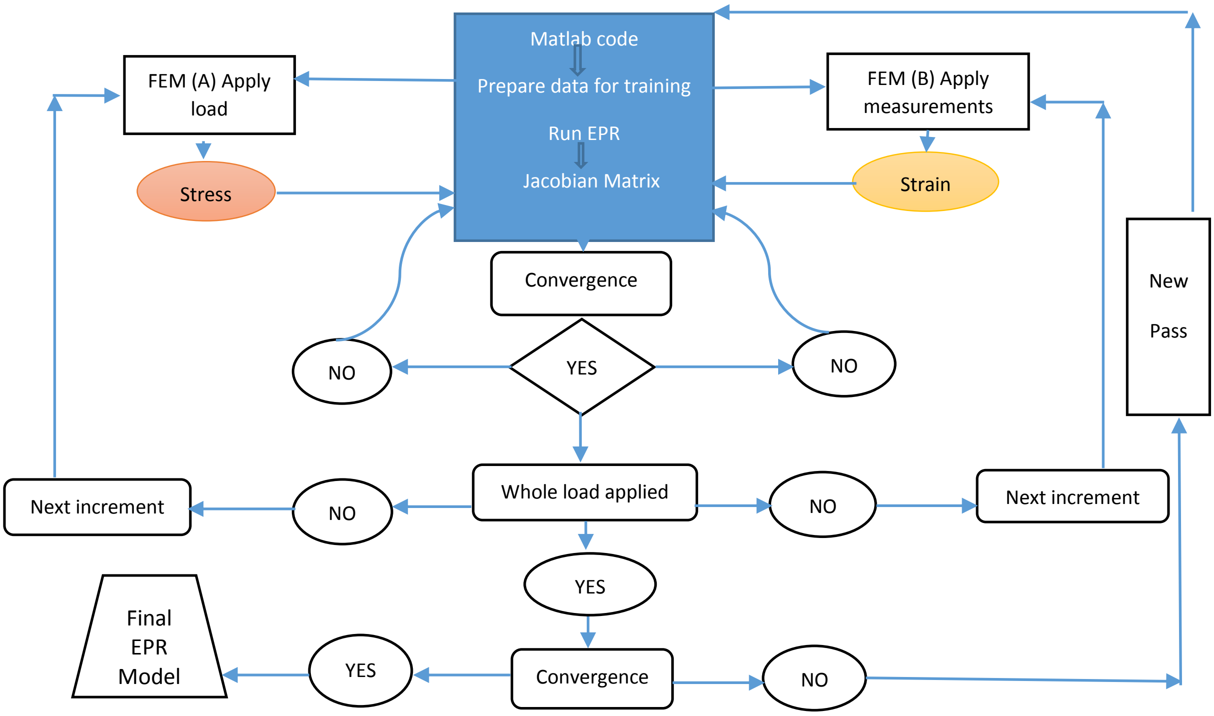

Figure 1. The flow chart of the proposed automation process of EPR-based self-learning FEM

4 – Numerical examples

4 – 1 Example 1

A 2D plane stress panel subjected to in-plane compression is considered. The geometry of the plate, boundary conditions and loading are shown in Figure 2. Due to the symmetry, only a quarter of the plate is simulated. The material of the plate is linear elastic with Young's modulus E = 500 pa and poison's ratio μ = 0.3 and the pressure applied is 10 pa. This example has been deliberately kept simple in order to verify the process of EPR based self-learning simulation.

The measurements are generated synthetically from a FE model using ABAQUS. It is assumed that during the experiment the displacements at the node on the right corner (node1) are recorded. Two finite elements models are created and three EPR models are used for the training process. Figure 3 shows the prediction of EPR-based self-learning FE model for the displacement at node (1) from one pass. Comparison is made between the results of the actual (linear elastic) model and the EPR based self-learning FEM. It can be seen that the EPR-based FEM is able to provide an excellent agreement with the actual data.

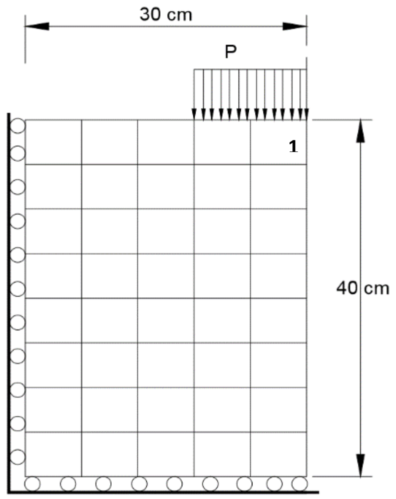

Fig.2 Geometry, loading, mesh and BC of the plate.

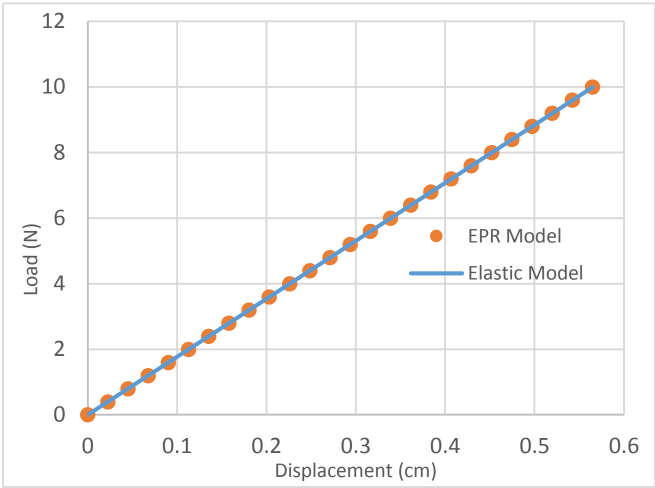

Fig. 3 EPR based self-learning FEM prediction at node1 1.

4 - 2 Example Two

A 2D truss structure with 13 axial force elements is considered in the second example. The geometry, boundary conditions and loading are illustrated in Figure 4. The truss is subjected to a concentrated load (100 KN) at node 3. The load–displacement data were generated using FE simulation with ABAQUS using the nonlinear Ramberg-Osgood model. The load and the corresponding displacement at node 3 are considered as the experimental measurements used in the self-learning process. The general form of the Ramberg-Osgood model is [6]:

$$\frac{\sigma}{E}+\frac{2\beta\sigma o}{3E}\left(\frac{\sigma}{\sigma o}\right)^{n}=\varepsilon \qquad (2)$$

Where E = 20.0×10^{9} pa, σ_o = 1.0×10^{7} pa, β = 2.34, n = 3.

The values of stresses were considered as input and strains as output. After training, in each run, an EPR model with the highest COD was chosen. It can be seen from Figure 5 that the EPR-based self–learning method is able to accurately capture the nonlinear behaviour of the truss from the first pass.

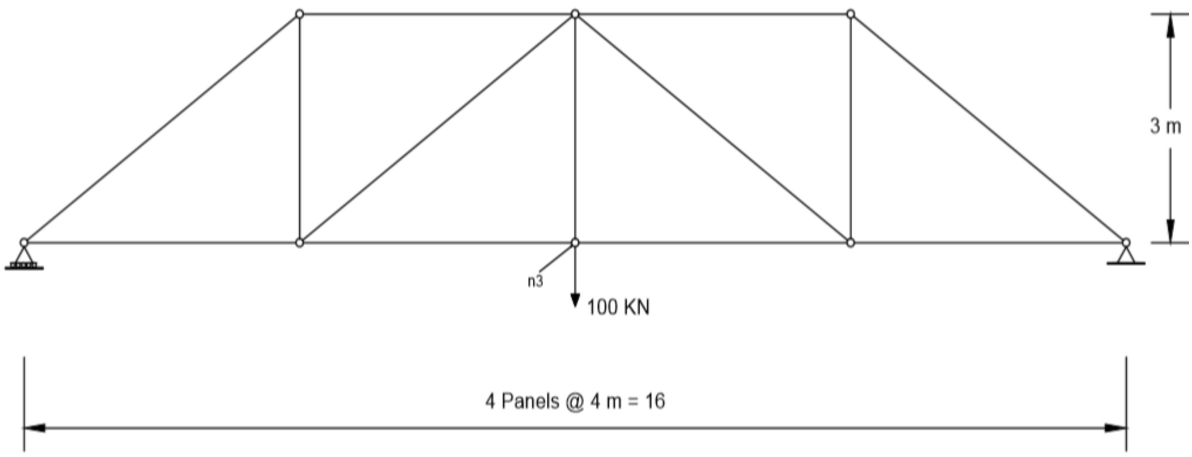

Fig. 4 Truss structure and the applied load

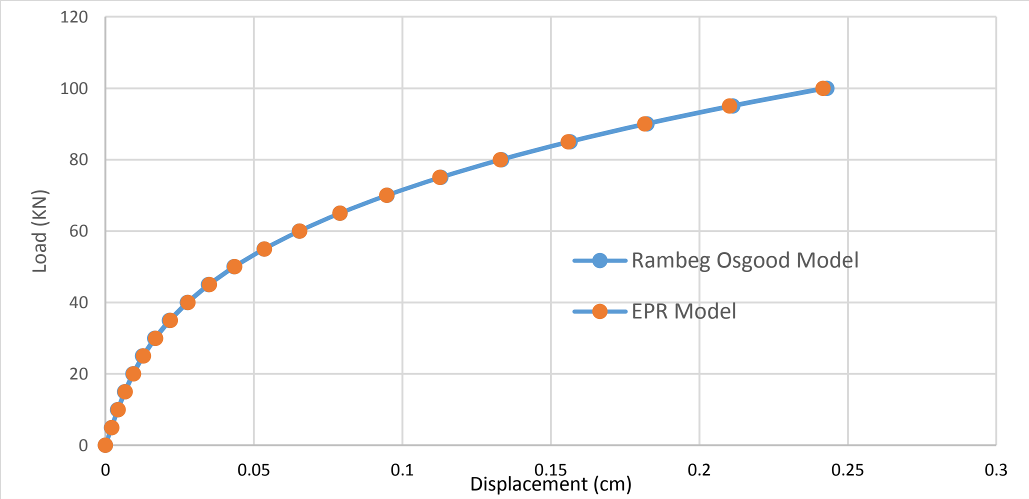

Fig. 5 Comparison between the Ramberg model and the EPR-based self-learning FEM (displacements at node 3)

5 – Conclusion

The conventional approach to constitutive modelling using data mining techniques requires a significant amount of data which could be costly and not available at all cases. Furthermore, obtaining a homogenous stress-strain state in experiments could be very challenging, especially for complex loading conditions. In this paper an EPR-based self-learning FE simulation model has been developed as an efficient approach for learning the constitutive behaviour of materials. The main advantage of using EPR in the self-learning FEM is that it gives transparent and structure equations representing the constitutive behaviour of material which can be readily implemented in FE code. The implementation EPR in the FE procedure is straightforward. In the self-learning FEM, there is no need to check yielding, to compute the gradients of plastic potential curve, to update the yield surface, etc.

The developed approach takes the advantages of the rich data buried in non-homogenous materials. It was shown that the EPR-based self-learning FEM is able to capture the material behaviour from one pass, reducing the overall computational time. In the two examples presented, the automation process was run only once and the EPR model captured the complete behaviour with very high accuracy. It should be noted that in more complex problems, more passes may be required to capture the more complex material behaviour. The proposed approach can be used in different boundary value problems.

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