Material Parameter Identification Using Artificial Neural Network

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Objective and scope

The objective of this work is to examine how neural networks can be used to reduce the computational time in the procedure for finding material parameters.

The aim of this work is to develop a method for determining the most appropriate material behaviour model for use in numerical simulation on the basis of experimental data, artificial neural network (ANN), genetic algorithm and finite element method (FEM) analyses.

Introduction

To make sure the result obtained from simulation procedures using finite element models are realistic it is crucial to have a material model that is as close to reality as possible. This is especially important when materials are subject to cyclic loads, because the difference in behaviour between actual materials and simulated models widens as the number of cycles increases (Lostado, Martínez-De-Pisón, Fernández, & Fernández, 2010).

The inverse identification procedure is a widely applied method for determining the appropriate material model. In this method a material test is first performed in a laboratory and then a FEM model is developed simulating the same test. Finally an optimisation procedure is used for adjusting the material parameters in the FEM model until the deviation from the two tests are acceptable. However as the number of material parameters to be identified increase the number of required FEM simulations becomes large making the procedure very time consuming. In recent years many researchers has put focus towards artificial intelligence and ANN for solving this problem (Hamdi, Hédi, & Ridha, 2011).

In this work a hybrid identification method using FEM, ANN and genetic algorithm is presented. This method is applied to identify the parameters in the Chaboche hardening model. The ANN is used as an alternative to FEM simulations in the optimisation procedure.

The Chacboche model

The Chacboche model is a hardening model describing how a materials resistance to plastic deformations increase when it is loaded beyond the yield strength. The model consist of two distinct components: a nonlinear kinematic component describing the translation of the yield surface via the backstress (α) and an isotropic component describing the size of the yield surface σ^0. The nonlinear kinematic hardening component for each backstress is given by the following equation:

$$\dot{\boldsymbol{\alpha}}_k = C_k \frac{1}{\sigma^0}(\boldsymbol{\sigma} - \boldsymbol{\alpha})\dot{\bar{\varepsilon}}^{pl} - \gamma_k \boldsymbol{\alpha}_k \dot{\bar{\varepsilon}}^{pl} \tag{1}$$

Where C_k and γ_k are material parameters and $\dot{\bar{\varepsilon}}^{pl}$ is the equivalent plastic strain rate.
The total back stress can be found by superimposing the backstress components.

$$\boldsymbol{\alpha} = \sum_{k=1}^{N} \boldsymbol{\alpha}_k \tag{2}$$

where N is the number of backstress components.

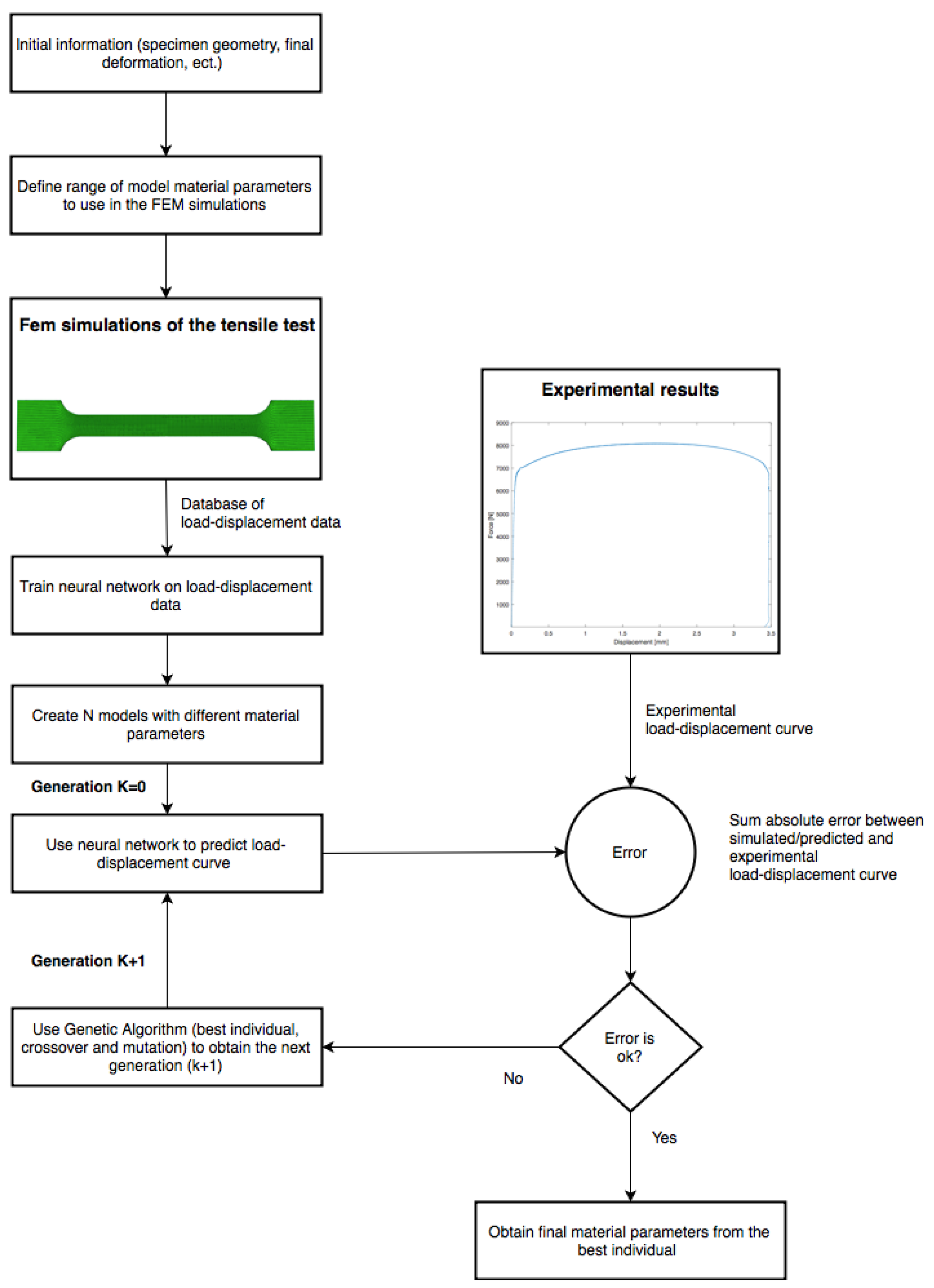
The isotropic behaviour of the model defines the expansion of the yield surface as a function of the equivalent plastic strain. It is implemented using an exponential rule and it is given by equation 3.

$$\sigma^0 = \sigma|_0 + Q_\infty(1 - e^{-b\bar{\varepsilon}^{pl}}) \tag{3}$$

Here $\sigma|_0$ defines the size of the yield surface at zero plastic strain. Q_∞ denotes the maximum change of size of the yield surface and b determines the rate the yield surface changes as the equivalent plastic strain develops.

Method

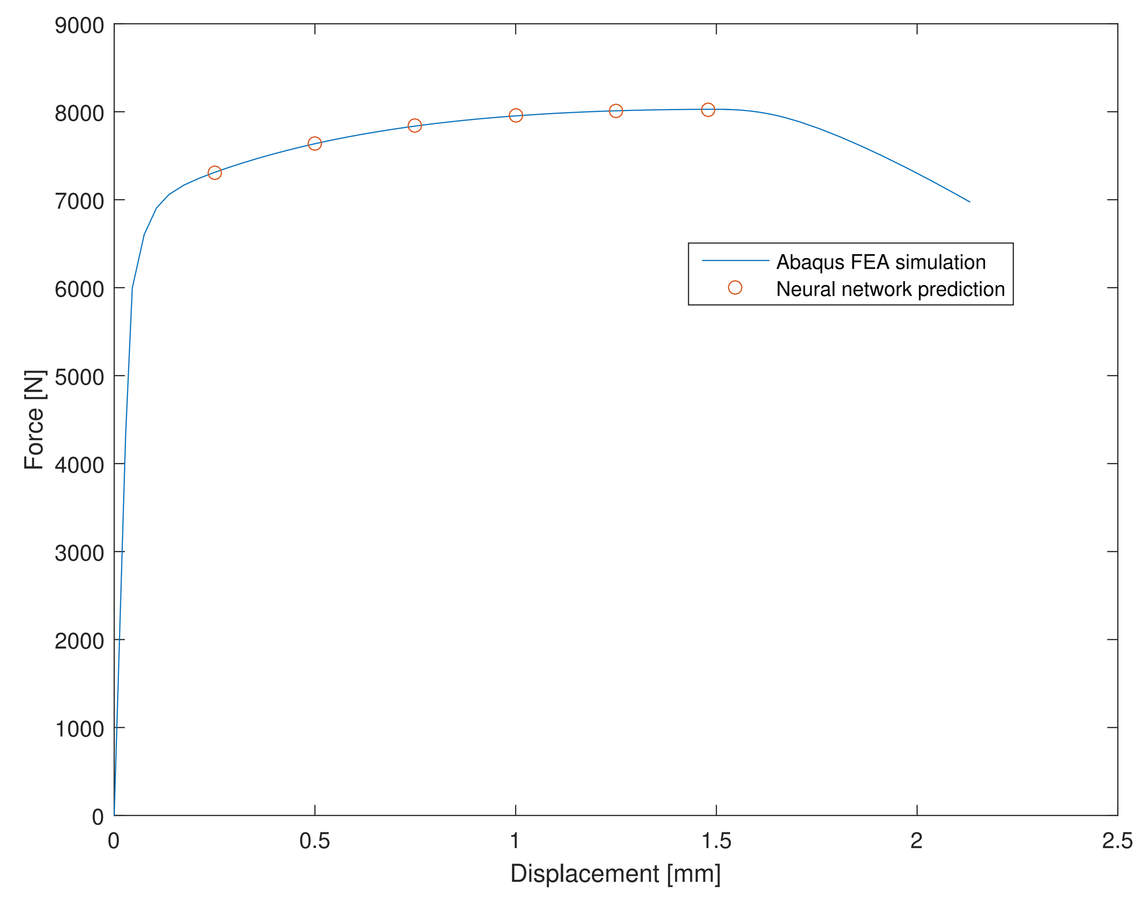
In the experimental test performed in the laboratory the test specimen was only loaded in tension so the Chaboche model describing the behaviour reduces to a nonlinear kinematic hardening model (equation 1 and 2). Furthermore initial FEM simulations showed that two backstress components were sufficient to reproduce the measured response from the experiment. The material parameters to be identified were then $\{C_1, \gamma_1, C_2, \gamma_2\}$. Where C_1 and γ_1 are the parameters for backstress component 1 and C_2 and γ_2 are the parameters for backstress component 2.



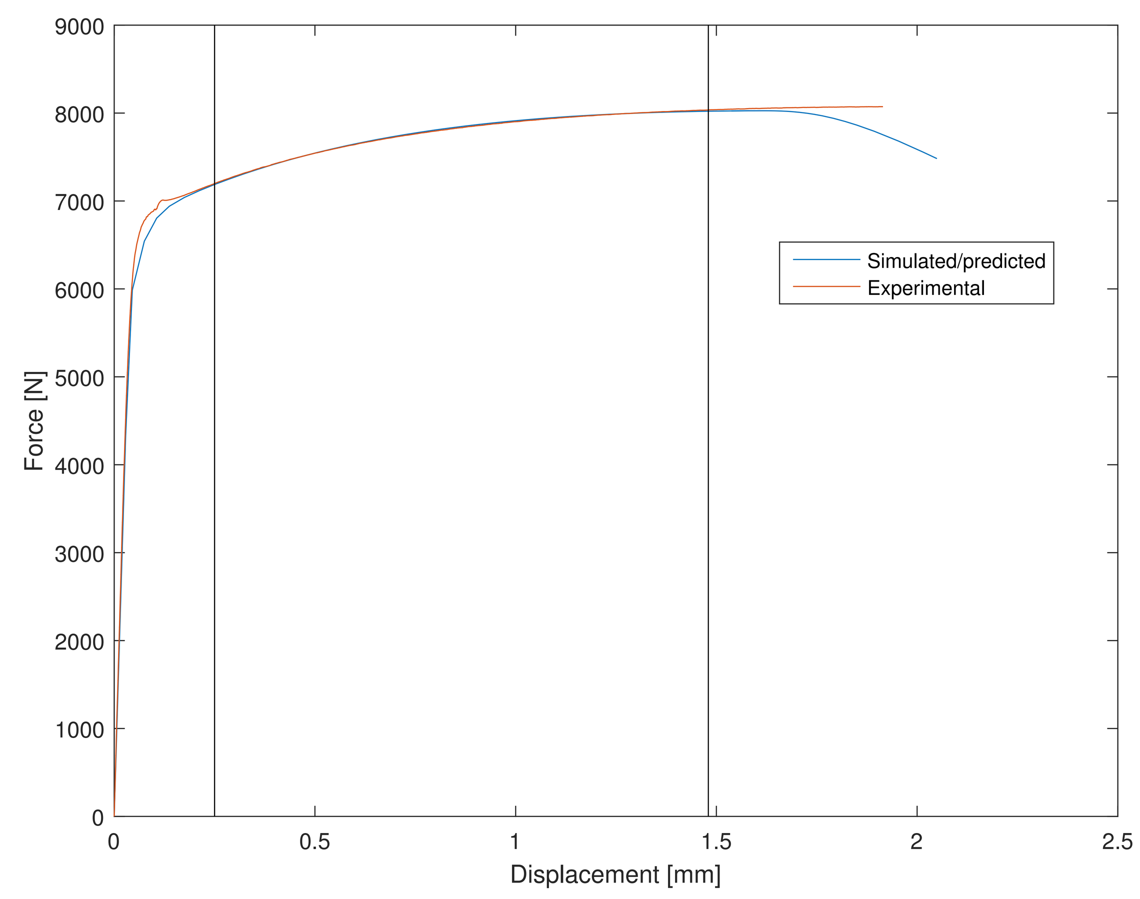
A flowchart illustrating the method for identifying the material parameters is given in the figure to the left. The method is based on a classical inverse identification procedure aiming to find the material parameters minimising the difference between a predicted response by FEM simulation and the measured response from experiment. However to save computational time the FEM simulations were substituted by an ANN in the optimisation loop. The FEM simulations were only used in the training of the ANN.

Results

The ANN was trained on a database of load-displacement data. The figure below shows a load-displacement curve obtained for a FEM simulation using an random generated material model and the predicted load-displacement curve for the same material model from a trained ANN. The figure illustrates that the ANN is able to predict the results from FEM simulations with high accuracy.



The figure below shows the load-displacement curve obtained from experiment and a FEM simulation using the material model found applying the proposed method. The simulated/predicted curve is optimised to minimise the difference between the two curves in the area between between the two vertical lines.



From the figure it can be seen that the simulated/predicted curve fits well in the area of consideration.

Comparison of the CPU time

The table below shows a comparison between CPU time for the proposed method using neural network and a classical inverse identification method.

	Proposed method	Classical methods
Training time for 500 simulations (min)	≈ 0.5	-
Population size	30	30
Number of generations	20	20
CPU time for one generation (min)	$30 * 0.0002$	$30 * 3$
CPU time for 20 generations (min)	$20 * 30 * 0.0002$	$20 * 30 * 3$
Total time (h)	≈ 0.01	≈ 30

The population size and the number of generations are parameters describing how many times the objective function is evaluated during the optimisation procedure. From the table it can be seen that the total computing time using the proposed method is very low compared to the classical method where finite element simulations are an integrated part of the optimisation procedure. In the comparison it is assumed that there exist a database of FEM simulations which be can used to train the ANN. However if a such database first has to be developed there won't be a large difference in the computational time between the two methods.

Conclusion

In this work a method for determining the most appropriate material behaviour model for use in numerical simulation is presented. The method has shown to be significantly less time consuming than the current practise given that a database of FEM simulations is available or if the method is to be applied to determine several similar material models.

References

Hamdi, A., Hédi, B., & Ridha, H. (2011). Parameter identification of an elasto-plastic behaviour using artificial neural networks–genetic algorithm method. *Materials and Design*, *32*.

Lostado, R., Martínez-De-Pisón, F. J., Fernández, R., & Fernández, J. (2010). Using genetic algorithms to optimize the material behaviour model in finite element models of processes with cyclic loads. *The Journal of Strain Analysis for Engineering Design*, *46*(2), 143–159.