REVERSE HOMOGENIZATION USING NEURAL NETWORKS FOR STRESS SHIELDING MINIMIZATION

Ana Pais (1), Jorge Lino Alves (2), Jorge Belinha (3)

1. INEGI - Institute of Science and Innovation in Mechanical and Industrial Engineering, Portugal; 2. INEGI, FEUP – Faculty of Engineering, University of Porto, Portugal, Country; 3. ISEP – School of engineering, polytechnic of Porto, Portugal

Introduction

One of the main concerns in implant design is stress shielding minimization. As bone regeneration occurs due to the a stress stimulus happening in the bone, a low stimulus caused by improper load transfer to the bone can lead to bone decay and further problems.

Porous geometries are commonly used in scaffold design for promoting cell adhesion and proliferation. Additionally, with porous geometries it is possible to tune the mechanical properties through topological design. [1]

The aim of this work is to achieve an optimal design by training the neural network so that for any given constitutive matrix it has as the output the optimal unit cell topology (Figure 1). The network is therefore able to reverse the homogenization procedure [2].

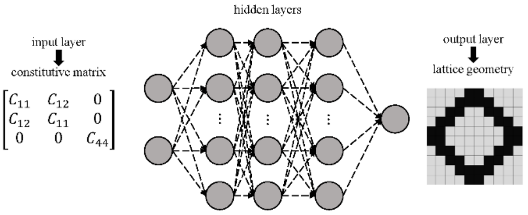

Figure 1 - Neural network scheme indicating the input and output data

Materials and methods

For a set of several different geometries, homogenization with periodic boundary conditions (PBC) was performed. A uniform mesh of square 2D elements allows to directly impose the PBC. The original geometry is therefore simplified to fit the uniform mesh. The linear-elastic analysis is run using ABAQUS as the solver.

A feed-forward neural network was created and trained in MATLAB. Each neuron i passes information forward in the network, according to (1)

$$z = f(b + wx) = f(b + \sum_{i=1}^{m} w_i x_i) \qquad (1)$$

where f is the activation function, b is the bias, w_i is the weight from the neuron in the previous layer and x_i is the value from the neuron in the previous layer. The training procedure adjusts the weights and bias by minimizing and error function for example the mean squared error (MSE).

The constitutive matrix was obtained by applying a unit strain in each of the three components (normal in the xx direction, normal in the yy direction and shear). Thus, the macro-stress tensor for each strain component provides a line of the constitutive matrix.

The macro-stress and macro-strain tensors are calculated through averaging theory

$$\overline{\sigma_{ij}} = \frac{1}{V}\int_V \sigma_{ij}\, dV = \frac{1}{V}\sum_{e=1}^{N_e}\sum_{g=1}^{N_g} v_g^e \sigma_{ij}^{e,g} \qquad (2)$$

$$\overline{\varepsilon_{ij}} = \frac{1}{V}\int_V \varepsilon_{ij}\, dV = \frac{1}{V}\sum_{e=1}^{N_e}\sum_{g=1}^{N_g} v_g^e \varepsilon_{ij}^{e,g} \qquad (3)$$

where V is the volume, v is the volume of the integration point, σ_{ij} is the stress component ij and ε_{ij} is the strain component, both evaluated at the integration point.

Figure 2 shows some examples of geometries from the training dataset.

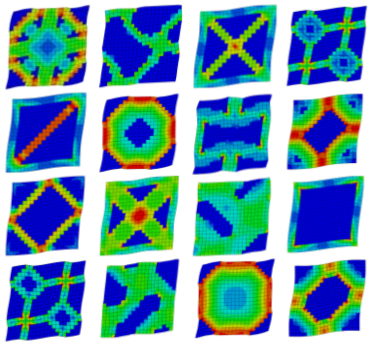

Figure 2 – Examples of geometries from the lattice dataset

Discussion

The NN allows for further optimization by taking as input the properties of bone, as shown in Figure 3. Therefore, it is possible to minimize the difference in mechanical properties between the scaffold and the bone in its surroundings, which leads to stress shielding.

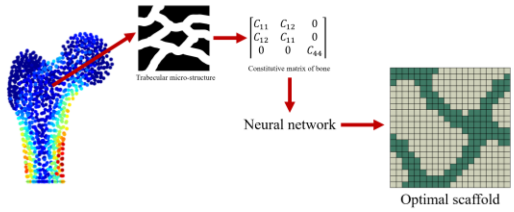

Figure 3 – Stress shielding minimization framework

References

[1] X. Wang *et al.*, *Biomaterials*, vol. 83, pp. 127–141, 2016,

[2] M. O. Elingaard et al., *Comput. Methods Appl. Mech. Eng.*, vol. 388, p. 114197, 2022,

Acknowledgements

The authors truly acknowledge the funding provided by LAETA, under project UIDB/50022/2020 and the doctoral grant SFRH/BD/151362/2021 (FCT, MCTES, State Budget, ESF, Por_Norte) under the MIT Portugal Program.