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Neural Networks for Bridging the Scales in a Multiscale Simulation of Concrete

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ABSTRACT

Macroscopic properties of materials with a heterogeneous microstructure are essentially determined by the constituents and their interaction on the lower scale. In the numerical simulations of these materials, two possibilities can be distinguished. One possibility is a phenomenological approach, where based on simulations on the fine scale or based on experimental results the parameters of a macroscopic material model are determined. This approach requires a suiteable material model, which has to be chosen from experience. The second possibility is the simulation on the fine scale, but a full model on the fine scale exceeds the computational power of current computers. In order to overcome this problem, multiscale approaches can be used, where only distinct regions are modeled on the fine scale, whereas most of the structure is modeled on the coarse scale. Although this approach can considerably reduce the computational effort, it requires a suitable coupling between the scales and certain transition conditions to decide at what point a transfer from the coarse to the fine scale is required. Especially in situations where the nonlinearity does not localize in certain regions this approach is as computational expensive as the full fine scale model.

In this paper, the derivation of a coarse scale material model based on neural networks is shown [1]. For the training of the neural network, representative numerical simulations on the fine scale are performed. This approach has the advantage that no a priori knowledge of the coarse scale material model is required. The complexity of the model is not limited, but iteratively determined in the training process.

In [2], neural networks were used as material models. In most methods using neural networks for the formulation of the material behaviour, the strains of an intergration point are the input of the neural network, whereas the current stress is the output. In order to model complex cycling loading additional input parameters are used as e.g. the stresses of previous equilibrium states and the strain differences to these states. But this approach limits the generalization capacity of the model, since the range of strain differences in the macroscale simulation must be covered by the fine scale simulations used for training.

In this paper, a different approach is proposed. The input parameters are the current strain and a history strain, which is in one dimension related to the maximum strain ever reached in the loading regime. In order to distinguish between loading and unloading, similar to a yield function in plasticity theory, a loading function approximated by a support vector machine is used. The mesoscale simulations used to

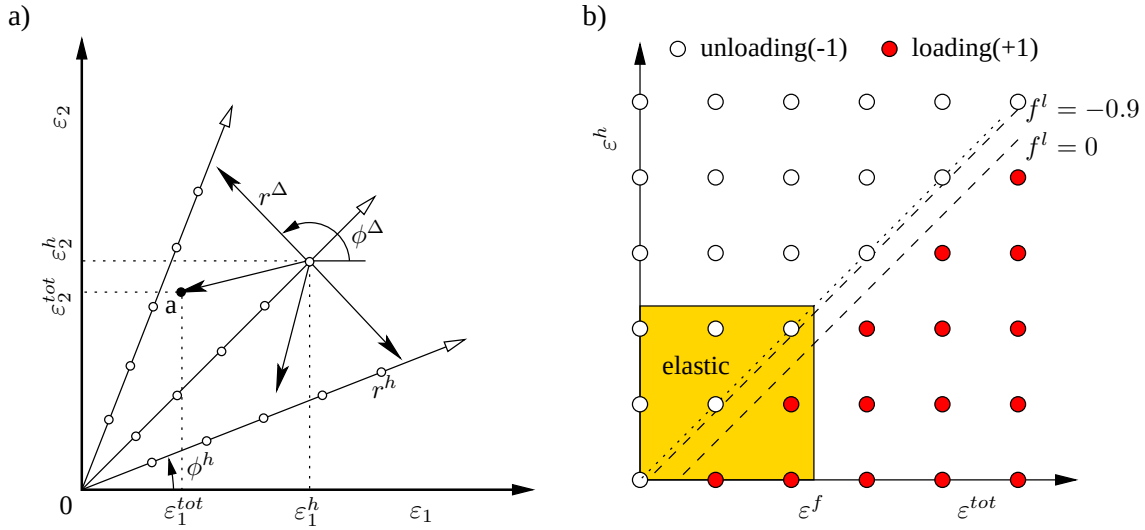

Figure 1: a)Generation of training samples and b)training samples for the loading/unloading network for a 1D tension test

generate the training data for the loading/unloading network are performed with different ratios between the strain components. These strains corresponding to the applied loads are incrementally increased up to a certain maximum history strain. From this history strain, additional strain increments are applied in radial directions as illustrated in Fig. 1a) in the case of two strain components. The decision, whether loading or unloading is observed, is based on the dissipated inelastic energy, where loading is interpreted as +1 and unloading as -1. The corresponding training data for a one dimensional tension test is shown in Fig. 1b). It is to be noted, that in the elastic regime, where the dissipated inelastic energy vanishes, a different criterion using the length of the strain tensor is used. Apart from the loading/unloading network, a second neural network modeled with a multilayer perceptron is used to approximate the stress as a function of the total strain and the total history strain. Consequently, the stress calculation is a two stage procedure. First, using the total strain and the history strain of the previous equilibrium iteration, a new history strain is calculated using the loading/unloading network. This procedure is similar to the return mapping algorithm in a plasticity formulation. In the second stage, using the total strain and the calculated history strain, the stress is extracted from the stress/strain network.

The procedure is illustrated using a 1D tensile test of concrete. The corresponding mesomodel is based on a combination of damage and plasticity (Drucker-Prager and Rankine) and shows softening behaviour. For models including softening, the size of the mesomodel is an important influencing factor, since a representative volume element (RVE) does no longer exist. Consequently, the dimension of the mesomodel is included as additional input parameter in the loading/unloading and the stress/strain network.

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