INTRODUCTION
It is well established that the form and function of (skeletal) tissues are linked such that the mechanical properties and microstructure of tissues are dependent on their loading history. It is of immense practical importance to be able to predict the response of tissues to a given set of loading. Two examples of the areas where such predictive capability is of great value are the design and post-operative analysis of orthopaedics implants and prediction of the tissue adaptation caused by disuse or prolonged exposure to microgravity. In such cases, the loading of the tissue is more or less known and one has to determine the response of a tissue to the specified loading. This is an example of the so-called ‘forward modeling’ and has been extensively studied in the literature. Inversely, one may be interested in determining the loading experienced by a tissue given the current state of the tissue. The actual state of tissue is (at least partly) determined by the loads the tissue experiences. An inverse problem should be solved: what are the inputs that have resulted in this given output? The solution of the inverse problem has several practical applications. For example, it can be used for noninvasive estimation of the musculoskeletal loads and determination of the characteristic of the daily activities that have resulted in a measured density distribution (applications are reviewed in [1]).

METHODS
In general, there is a nonlinear mapping between the space of the loads applied to the bone tissue and the tissue architecture that is a consequence of that loading. The response of the tissue to the applied load is represented in our model as the spatial distribution of the density (porosity) of the tissue. Two mappings can be defined in this relation. The first mapping is called the ‘forward mapping’, because this mapping goes forwards in time and predicts the spatial density distribution that results from a specific set of loading parameters. The inverse of forward mapping goes backward in time. Given a certain spatial density distribution, the so-called ‘backward mapping’ determines the set of loading parameters that has resulted in the given spatial distribution of density, thereby mapping the space of density distribution to the space of loading parameters. The forward mapping can be easily constructed using the FEM model together with the tissue adaptation algorithm. For any set of loading parameters, the FEM model can calculate the resulting spatial distribution of the density based on the solution of the tissue adaptation equations. In this study, the forward mapping is constructed in this study by using a tissue adaptation model that is similar to the one presented in [4].

Artificial Neural Networks (ANNs) were selected to establish the backward mapping. This choice was motivated by the special properties of ANNs. It is mathematically proven that a feedforward ANN with at least one hidden layer, \( n \) hidden neurons, and sigmoid activation functions can approximate any continuous function with an integrated squared error of
order $O(1/n)$, regardless of the dimension of the input space [5].

In order to analyze the proposed load identification technique, the problem of tissue adaptation of trabecular bone is considered in this study. The geometry, boundary conditions, and loading parameters are similar to the ones used in [6] and are presented in Figure 1a. For a given set of loading parameters, $F1-F4$, the forward tissue adaptation model calculates the resulting density distribution. An example of the density distribution that can be determined by the forward model is presented in Figure 1b. An Artificial Neural Network (ANN) was used for identification of the load from a given set of density distribution in a way illustrated in Figure 1c: The ANN receives the density distribution as input and returns the loading parameters, $F1-F4$, as output. The ANN should be trained using a training dataset. The training dataset consists of a series of runs of the forward model for a number of chosen loading parameters. For this training dataset, both the density distribution and the loading parameters are known. The ANN is trained such that for any given density distribution in the training dataset, it returns the corresponding loading parameters. The ANN can be then used for identification of the loading parameters in cases that were not used in its training.

**RESULTS AND DISCUSSION**

The ANN learns the backward mapping rapidly. The identification error decreases by 5 orders of magnitude in less than 100 training iterations (Figure 2a) and the correlation coefficients, $R$, reaches 1 (Figure 2b). Only 90% of the training dataset is used for the training of the ANN (Figure 2b). The other 10% is used for validation and testing of the ANN, showing that the ANN can successfully identify ($R=1$) the loading cases that were not used in its training (Figure 2c).

![Image](image.png)

**Figure 1:** A schematic drawing of the loads and boundary conditions of the model studied in this paper [6] (a), an example of the density distributions that can be determined using the tissue adaptation model (b), and a schematic illustration of the load identification procedure (c).

The results of this study imply that artificial neural networks can be used as a tool for identification of the loads that are experienced by tissues during the tissue adaptation process. Even with a relatively small size of the training dataset, the accuracy of the load prediction is excellent: identification error is less than 0.01%.

**CONCLUSIONS**

Artificial neural networks can accurately and efficiently identify the loading parameters of tissue adaptation problems, given the density distribution of the tissue.

**REFERENCES**