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Artificial neural networks and intelligent finite elements in non-linear structural mechanics

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ABSTRACT

In recent years, artificial neural networks were included in the prediction of deformations of structural elements, such as pipes or tensile specimens. Following this method, classical mechanical calculations were replaced by a set of matrix multiplications by means of artificial intelligence. This was also continued in finite element approaches, wherein constitutive equations were substituted by an artificial neural network (ANN). However, little is known about predicting complex non-linear structural deformations with artificial intelligence. The aim of the present study is to make ANN accessible to complicated structural deformations. Here, shock-wave loaded plates are chosen, which lead to a boundary value problem taking geometrical and physical non-linearities into account. A wide range of strain-rates and highly dynamic deformations are covered in this type of deformation. One ANN is proposed for the entire structural model and another ANN is developed for replacing viscoplastic constitutive equations, integrated into a finite element code, leading to an intelligent finite element. All calculated results are verified by experiments with a shock tube and short-time measurement techniques.

1. Introduction

Artificial neural networks have been applied in engineering problems as an alternative approach compared to classical methods based on continuum mechanical modelling. Promising results were achieved by investigating stress-strain curves of metal specimens under high-temperature [1], design of steel structures [2], vibrations of structures [3,4], or stability problems of structures [5]. Reliability studies of structures were reported in [6] and influences of welding on material properties are investigated in [7]. An ANN can lead to much lower computational time and can replace the mechanical model completely. It can be trained by experimental data, only, and needs therefore no identification of material parameters. Consequently, a mathematical model is generated by means of an algebraic system of equations. Following this approach, the ANN approximates to the trained data. The learning procedure of the ANN is based on the examples, which are provided by the user [8]. However, weaknesses of ANNs have been reported in [9] due to the difficulties of interpreting parameters in neural networks, e.g. the number of hidden layers or neurons. Also the components of the synapse matrices of a trained ANN can hardly be interpreted as it can be done with material parameters in a constitutive law. In several studies, the problem of a so-called black box is described [10,11]. Consequently, it is difficult to find reasons to explain discorrelations between predictions using ANN and experimental data. Once, the ANN has been trained well with input and output data sets, it can recalculate the provided data very accurately. However, predictions beyond that data can lead to uncertain results, which is documented in literature [12]. An additional approach using the advantages of ANN together with well-established numerical methods is the development of intelligent finite elements. These elements have been proposed in literature, leading to a combination of classical finite elements with an ANN and are used only for a part of the entire mechanical model. Studies substituting the constitutive model by means of an ANN have been published in [13]. A beam element, based on a neural network, is proposed in [14] and leads to lower computational costs than a classical approach. This benefit is even more pronounced since multiscale approaches are concerned [15]. In literature several neural network constitutive models (NNCM) were discussed [16]. However, it was reported that the choice of the provided training data is essential for a reliable intelligent finite element [17].

The substitution of nonlinear structural and material models for two-dimensional structures by ANNs is, to the knowledge of the authors, not yet well known in literature. Structures, such as plates and shells, are widely used in engineering, can be subjected to dynamic loadings and can undergo geometrically non-linear deformations with inelastic strains. Especially, the correct modelling of strain-rate dependency of structural deformations is subject of current research [18–20]. In the present study, metal plates are loaded impulsively by

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shock waves causing viscoplastic deformations and high inelastic strain rates. The aim is to propose an ANN, which is able to predict these highly non-linear structural deformations. The ANN is developed in two ways. Firstly, a neural network is proposed, trained by experimental data only and, afterwards, it is used to predict structural deformations in additional experiments. Secondly, in order to overcome discorrelations between measurements and calculations, an intelligent finite element is proposed, wherein the constitutive equations are replaced by an ANN. This neural network is trained with data about stresses, strains, strainrates and hardening in a range, which is expected in the finite element simulations. Following this strategy, we exploit the advantage of ANNs to be very accurate since only trained data is used. The intelligent finite element is implemented in a code for a geometrically non-linear first-order shear deformation shell theory. In this way, a classical shell theory is combined with an ANN substituting a physically nonlinear constitutive law and leading to low simulation times. By means of the proposed method, ANNs shall be accessible to nonlinear structural problems in engineering.

2. Experiment

The measured results of structural deformations are obtained by experiments in a shock tube, see [21]. In Fig. 1, the used set-up of the shock tube is shown, consisting of a high (HPC) and a low pressure chamber (LPC), separated from each other by an aluminum membrane. After an increase of the gas pressure in the HPC, the membrane is destroyed, causing a shock wave, which propagates the shock tube towards the aluminum plate specimen in the LPC. If the shock wave hits the plate, then a high-pressure and high-density impulse is caused on the specimen leading to viscoplastic deformations in time scales of several microseconds.

The mid-point displacement of the circular specimen and the pressure acting on the plate during the time are measured by means of short-time measurement techniques. The experiments are carried out with different thicknesses of membranes between the HPC and LPC and with different gases in the HPC, such as nitrogen and helium. In this way, different pressure peaks (pp) and pressure evolutions can be caused on the specimen. The plate specimens are 2 mm thick and exhibit a diameter of 553 mm. In Fig. 2, four experiments with mid-point displacements (Dis.) of the plates and pressures (Pre.) acting on them are presented. Three of them will be used to train the ANN and the fourth one is taken as a reference for the validation of the ANN. The measurements can be recorded down to 1 μs sample rate in order to assure that enough experimental data is available to train the ANN. The capacitive displacement sensor, developed in [21] and the piezoelectric pressure sensors exhibit an inertia small enough to record fast signal changes.

3. Artificial neural network for the entire structure

The ANN developed in this study is based on a feed forward network, which is well established in literature [22]. The present

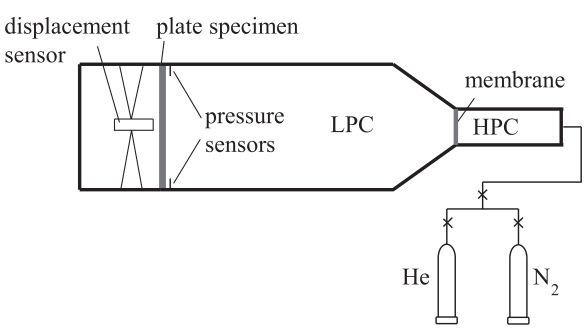

Fig. 1. Principle of the shock tube.

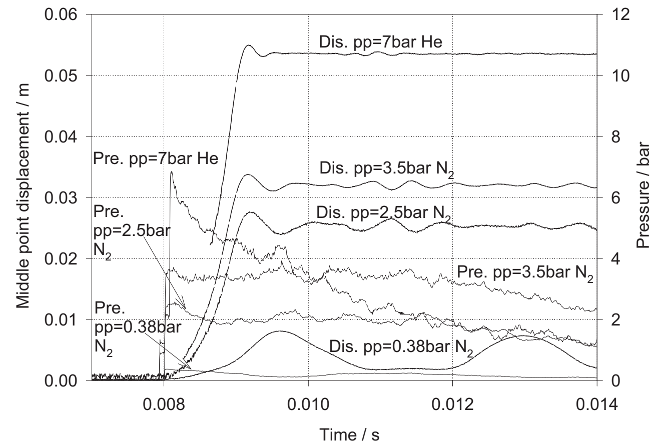

Fig. 2. Plate deflections under high speed pressure loadings with peak pressures (pp) at the specimen and helium and nitrogen in the HPC.

algorithm consists of three layers and is implemented in python. The input layer includes three neurons, representing time, pressure, and shock wave propagation velocity. The hidden layer is composed of eight neurons and the output layer has one neuron denoting the mid-point displacement of the plate specimen. In incremental approaches, as in the finite element method, increments of state variables, e.g. strains and displacements, are accumulated during the simulation. However, in the present study, the ANN uses ordered pairs of values with the mentioned input and output values, i.e. one pressure, one mid-point displacement, and one propagation velocity can exist only at one instance of time. If we ignored one of these neurons, then ambiguous solutions would be possible. For this reason, the time is treated as a state variable in the ANN as e.g. the mid-point displacement.

In Fig. 3, the architecture of the ANN is shown. In order to optimize the least square error between calculated output and provided output data, a gradient descent algorithm in form of the back propagation method is applied. All values used in the ANN are normalised due to better convergence [1,23]. In [24], it was described that it is necessary to obtain numerical stability with homogeneous values. Here, this is carried out for input and output values x_i by

$$X_i = 0.1 + 0.8\cdot\left(\frac{x_i - x_{min}}{x_{max} - x_{min}}\right)$$

leading to unified values X_i and with x_{min} and x_{max} as minimum and maximum values of each input and output value, respectively. The propagation function includes the weights w_{ij}, which exhibit random values initially. They represent the weights of the connections between

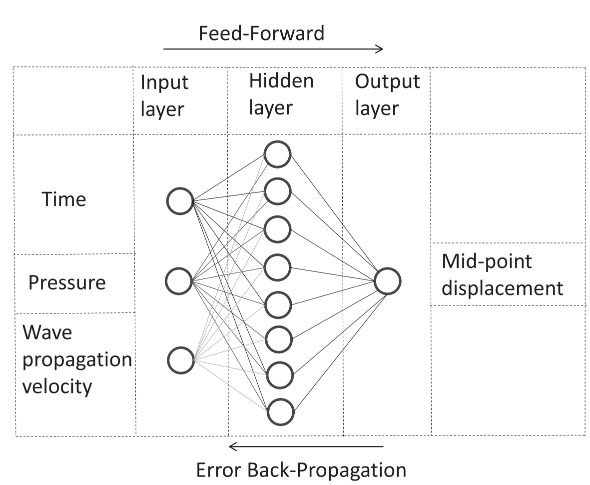

Fig. 3. Artificial neural network for the entire structure.