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DEEP LEARNING METHODS FOR THE ACOUSTIC EMISSION METHODS TO EVALUATE AN ONSET OF PLASTIC STRAINING

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Abstract: *Development of phenomenological plasticity models, hardening rules, and plasticity theories relies on experimental data of plastic straining. The experimental data are usually measured as the stress–strain response of the material being loaded and do not provide any clues or information about the local response of material. In this paper, we analyze the plastic deformation of the material using the acoustic emission method and current state-of-the-art neural network models such as the InceptionTime architecture.*

Keywords: Metal plasticity, Strain hardening, Acoustic emission, Neural networks.

1. Introduction

Phenomenological plasticity models are commonly implemented in various FE codes. The models are crucial to design, analyze, and assess engineering structures with respect to various damage modes and other related phenomena, e.g., static overloading, ratcheting, low cycle fatigue, and residual stresses. *Cf.* Welling *et al.* (2017) and Halama *et al.* (2008). From the experimental point of view, metal plasticity is mostly related to permanent strains and determined by reaching a prescribed strain threshold. In some applications where the plastic strain onset needs to be precisely determined, the plastic strain might be determined as the deviation of linear elastic behavior of material, see Wu and Yeh (1991) and Štefan *et al.* (2021).

However, experimentally, strain is usually measured globally and assumed to be uniform in a region of interest. Therefore, local information about plastic deformation is lacking. Further, metals manifest various strain hardening mechanisms some of which can be observed by advanced experimental techniques only. *Cf.* Parma *et al.* (2018) and Marek *et al.* (2022). Therefore, it is appropriate to use additional experimental methods independent of global strain measurement to analyze plastic straining of metals, evaluate strain hardening, and, possibly, calibrate models.

In this work, we have employed an acoustic emission method to experimentally analyze plastic straining of material under uniaxial loading. See Kovanda (2021). Acoustic emissions (AEs) are transient elastic waves that occur in solids due to dynamic changes within the material. AEs are usually detected on the surface of the material. Traditionally, measurement of surface displacement caused by the dislocation slip within the material using an AE method is very demanding and requires precision in the AE measurement. However, now, AE can be extensively studied due to the great advances in bulk data processing and the availability of ultrasonic measurement equipment. AE together with machine learning methods offers a promising tool for plasticity detection. In this paper, an artificial neural network (ANN) architecture was trained to detect the onset of plastic deformation based only on a section of continuous emission signal recording. Its results are demonstrated on real data.

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2. Experimental setup

The specimens were loaded on axial-torsional testing system of Instron 8852 type. The testing system consists of a universal hydraulic testing machine, hydraulic power unit, control unit, and personal computer. The system has an axial load capacity of ±100 kN. The testing procedure was designed in the proprietary software Bluehill Universal by Instron company. Strains were measured by AVE-2 Non-Contacting Video Extensometer also supplied by the Instron company. To dampen the noise of the hydraulic system of the testing machine, special polyamide thin plates were used to acoustically separate the wedge grips from the machine frame. Concerning AE equipment, two piezoelectric sensors (Dakel IDK-9) were glued to the surface of the material to measure elastic waves and convert them into electrical signals. The signal path also contained preamplifiers (PAC 2/4/6) to suppress interference. Finally, a USB oscilloscope (TiePie Handyscope HS6) was used for continuous recording of the emission signal (see Fig. 1).

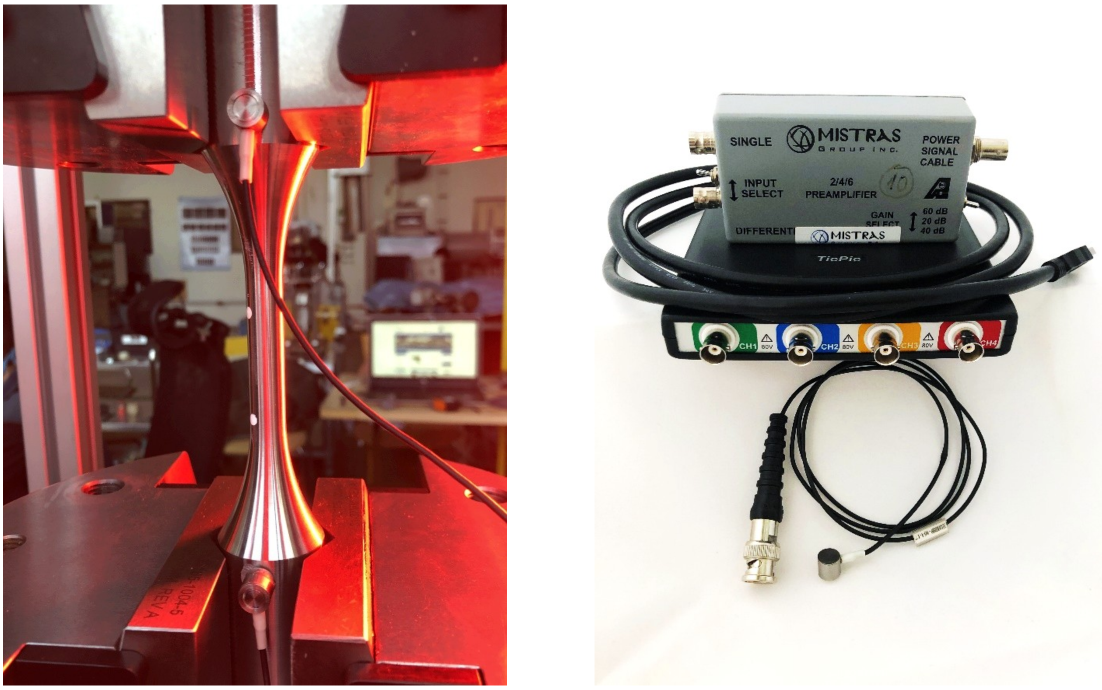

Fig. 1: Specimen in testing machine, USB oscilloscope, AE preamp and sensor.

3. Neural network implementation

All tested neural network architectures were created in the Keras library of the Python environment with the tensorflow backend, as it is well established and optimized for training on GPUs. Training on a GPU instead of a CPU is essential to speed up the process. For this reason, an NVIDIA GEFORCE RTX 2070 graphics chip with 8GB of memory was used for training and evaluation. Another reason for using these libraries is that they are widely used by researchers and developers around the world. It's also worth noting that there are multiple Python libraries designed to handle neural networks, such as the PyTorch library, which is becoming increasingly popular since 2021. Both libraries offer a good background for creating neural networks with many state-of-the-art models already implemented.

To analyze the whole length of experimental data, the training and validation intervals are chosen from both the plasticity and elasticity part of the measured signal, as described in Fig. 2. These parts were determined by expert estimates of the highest probability of occurrence or absence of plastic deformation in the respective time windows. After successful training, resulting networks evaluated the emission signal over its entire length, corresponding to the duration of the tensile test. The output symptom vector then responds in some way to indications of plastic deformation in the input signal. The success rate of the networks at the times between training intervals can then be discussed with respect to the evolution of the load curves.

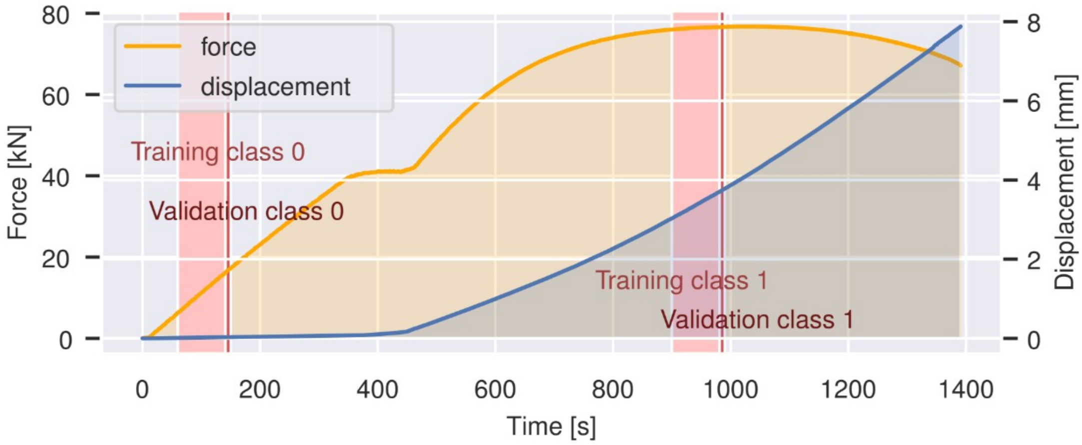

Fig. 2: Force and displacement curve – data from testing machine.

All architectures created need a well-defined input shape. For 2D convolutional networks, the input must have three dimensions, and for 1D convolutional networks, two dimensions. The last dimension consists of the different measured channels, if available. In the described experiment, two channels were available, i.e. a continuous signal from two AE sensors, see previous section. In order to use 2D convolutional networks, the signal must be transformed using a suitable time-frequency transform. This presents a certain disadvantage of these architectures in the form of the time-consuming computation of input data with sufficient resolution, e.g. continuous wavelet transform or spectrogram with a selectable frequency axis.

The next model investigated is the InceptionTime architecture, which takes as input a section of the signal itself. This model had by far the best results and is stable even with respect to the requirements for manually selected hyperparameters. Since the measured signal is continuous, the input can be taken from any position in the training intervals. This allows an extensive set of input tensors (or arrays) to be created, all of which are distinct. This approach can help reduce overfitting.

In order to fit the network from the raw or transformed data, Python generators were created. These generators take all the input data and generate individual inputs that match the network input size from determined intervals. This significantly reduces the memory demand because these generators do not use any memory until the particular data is needed. After their usage the memory is freed, and another data is created.

4. Signal evaluation

Three generators were made in order to train the network, evaluate the network and evaluate all the signal. The first two mentioned generators are configured so that it would generate data from randomly sorted set of starting coordinates solely from one channel. The number of coordinates is chosen manually and since all the generated data are different, all the training is processed in only one epoch.

The generator for the signal evaluation is created so that the individual data would not overlap. This decision was made in order to reduce the evaluation time. Furthermore, experiments show that signal evaluation results (output symptom vector) are in general very unstable, so the results are smoothed using a Gauss window with manually chosen deviation.

Figure 3 illustrates the smoothed output of eight different trained versions of the same network architecture. These results also show that the InceptionTime model is not as sensitive to the initial weights as many other architectures. All the predictions are almost identical with only a little difference in their scaling. There is also a clear increase in the symptom vectors values (outputs of the networks) from zero to one in the time corresponding to the deviation of the loading force (orange curve) from the linear trend. Since the validation score on these data is exactly 100% on all eight trained networks, the InceptionTime model was determined to be best for given task.

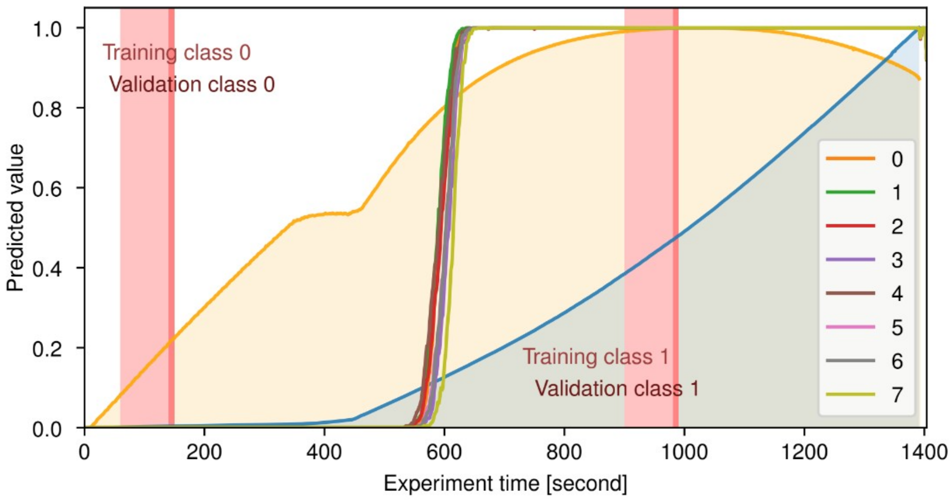

Fig. 3: Results of the InceptionTime model applied to whole recorded signal.

5. Conclusions

Among the other ANN architectures tested, the InceptionTime model performs best in the task of detecting dislocation slip in the metallic material sample under tensile testing. Moreover, this architecture predicts reliable values for a signal measured on a different part of the material and even for a signal from a different experiment. This makes the InceptionTime architecture the best studied model capable of detecting the onset of plastic deformation. This network also does not require any time-frequency transformation because it is applied to the raw signal.

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