

# COMPARISON OF DIFFERENT APPROACHES CONSIDERING PHYSICAL PROPERTIES IN ANN MATERIAL MODELING FOR PLASTICITY

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## ABSTRACT

For more than thirty years, classical material modeling is accompanied by data-based approaches in order to circumvent the traditional definition of analytical material functions and the subsequent fitting of their material parameters. So-called data-driven approaches no longer define material functions at all, by embedding experimental data directly into the numerical analysis. Other methods aim to construct a machine-learning based constitutive model from the experimental data a priori, in order to use it afterwards within the numerical analysis. Both approaches have their advantages and disadvantages. In our contribution, we follow the second method and use feedforward artificial neural networks (ANNs) to construct a material function for rate-independent plasticity. ANNs are well suited for this application since they are universal functional approximators. While training ANNs on data directly, no physical properties, e.g., material stability or the dissipation inequality are considered. Therefore, in recent years, several approaches enhanced the purely data based training of ANNs considering physical properties. For example, in [1], constrained optimization techniques are used to enforce physical constraints in a weak sense during the training process. In [2], a special ANN architecture is used to ensure polyconvexity for hyperelastic ANN material models; these architectures can also be used for plasticity. In our presentation, we compare different approaches to account for physical properties in ANN material modeling, especially when applied to plasticity. In addition to the comparison of the compliance with the physical constraints, the required amount of data is also taken into consideration. The trained ANNs are used within Finite Element calculations of metal structures in order to evaluate their performance qualitatively and quantitatively.

## REFERENCES

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