Data Driven Modelling of Crash Barriers Combining Multiscale Analysis and Physics-Based Feed Forward Neural Networks

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The systematic and reliable assessment of the crash safety performance is a corner stone of the automotive design process. This simulation-based analysis relies on validated and robust crash barrier models. Depending on the crash scenario, the barriers are assembled from multiple aluminium honeycomb blocks. Each having specific constant or progressive strength properties.

ESI Group, as a virtual prototyping partner, is providing validated compute models of such barriers to its customers. While a scale-one model of the honeycomb structure is not feasible due to the required computing time, a shell-based reduced representation of the barrier structure is currently used to provide computationally efficient and accurate models. A further reduction of the computational cost is currently examined by making use of data-driven material models. Here, machine learning (ML) algorithms like neural networks are used to build effective constitutive relations for complex structures such as honeycombs.

The data basis for the ML algorithms is generated using a high-fidelity multiscale analysis in combination with homogenization techniques. In the present contribution, a physics-based feed forward neural network is used to describe the effective material behaviour of the honeycomb. The analytical basis of neural network and the subsequent differentiability allows for a straightforward implementation of fundamental thermodynamic relations into the network architecture.

The generic implementation of the neural network evaluation functions in a commercial Finite Element code allows for the direct application of the data-driven effective material model to industrial relevant problems. The performance of the generated model is analysed in terms of accuracy and computational efficiency.