

# Physics-informed neural networks derived from a mCRE functional for constitutive modelling

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## Abstract

The damage of mechanical structures is a permanent concern in engineering, related to issues of durability and safety. The theme is currently the subject of various research activities; a typical example is the ERC project DREAM-ON (2021-2026), in which this work is involved, which focuses on complex mechanical structures in composite materials and aims to address the numerical challenges related to integrated health monitoring of large-scale structures, in order to move from smart materials to smart structures, able to monitor their condition autonomously and operate safely even in degraded mode. More specifically, the work addresses a particular challenge of the ERC project; it aims at building an efficient numerical procedure for the assimilation of data from distributed fiber-based sensors. The idea is to create a hybrid numerical twin, combining physical models (which represent a rich history of engineering sciences, and which provide a strong a priori knowledge) and learning techniques from AI (here, neural networks). The latter techniques are thus exploited here to correct the model bias, and not to substitute it as in full data-based approaches. However, classical neural networks (in the sense that they are not informed by physics), have the disadvantages of requiring very large volumes of data to be trained, as well as decreasing accuracy when generalizing to new data. Physics-informed neural networks [1, 5] have been used to overcome these obstacles in various applications [2] because learning is simplified (experimental richness being added to prior knowledge). Here, a method using neural networks for learning behavior laws in the form of thermodynamic potentials is proposed. In this approach, the architecture of the network satisfies thermodynamic principles [4] thanks to computation of some quantities by automatic differentiation as well as convexity properties imposed in the neural network structure. Additionally, the learning of the neural network is facilitated by the use of a physical cost function, the modified constitutive relation error already used in the context of parameter updating [3]. The methodology will be illustrated and analyzed on different test cases.

## References

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