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ON THE THERMODYNAMIC ADMISSIBILITY OF DATA-DRIVEN COMPUTATIONAL MECHANICS

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We explore in this work the issue of thermodynamic admissibility of data-driven computational mechanics. In previous works, see [1, 2] we defined the problem as the one of establishing a constitutive manifold from machine learning techniques. In this work we pursue the establishment of thermodynamically sound techniques that satisfy fundamental principles such as the conservation of energy and positive dissipation of entropy.

Particular emphasis is put on the use of machine learning and model order reduction techniques that are exploited to identify the plastic behaviour of a material, opening an alternative route with respect to traditional calibration methods. Indeed, the main objective is to provide a plastic yield function such that the mismatch between experiments and simulations is minimized. Therefore, once the experimental results just like the parameterization of the plastic yield function are provided, finding the optimal plastic yield function can be seen either as a traditional optimization or interpolation problem. It is important to highlight that the dimensionality of the problem is equal to the number of dimensions related to the parameterization of the yield function. Thus, the use of sparse interpolation techniques are very promising.

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