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The Value of Scientific Machine Learning for Geothermal Applications

Denise Degen[1], Mauro Cacace[2], s.Mohammad Moulaeifard[1,3], and Florian Wellmann[1]
[1]RWTH Aachen University, Computational Geoscience and Reservoir Engineering, Aachen, Germany
[2]GFZ German Research Centre for Geosciences, Telegrafenberg, Potsdam, Germany
[3]RWTH Aachen University, Department of Engineering Geology and Hydrogeology, Aachen, Germany

For geothermal applications, we aim to obtain an understanding of the physical processes in the subsurface, to predict the geothermal potential reliable. Naturally, the reliability of the prediction of the physical processes directly relates to the reliability of the evaluation of the geothermal potential. Unfortunately, predicting the physical processes reliable is a non-trivial task because of high uncertainties related to these processes. These uncertainties may arise, for instance, from uncertainties of the rock properties (e.g. thermal conductivity, permeability), structural uncertainties, and not considered physical processes.

Considering the various sources of uncertainties yields a high-dimensional and therefore computationally extremely demanding problem that is not solvable even with state-of-the-art high-performance software packages. To address this curse of dimensionality, we employ a methodology, namely the non-intrusive RB method, combining advanced mathematical algorithms and machine learning methods. This method aims to significantly reduce the dimensionality of the problem while maintaining the physical principles. In contrast to other machine learning methods, the method produces interpretable and scalable models, which are crucial to obtain reliable and robust predictions.

In this work, we show how the method constructs surrogate models for coupled geothermal applications, which allow, in turn, the performance of global sensitivity analysis and uncertainty quantifications. Both methods are essential for improving our model understanding. Furthermore, we demonstrate how the method in combination with developments from the field of computer graphics (e.g. NURBS, and subdivision surfaces) can be used to quantify the influence of structural uncertainties on the temperature distribution.