XI International Conference on Coupled Problems in Science and Engineering, COUPLED 2025
May 26-29, 2025, Villasimius, Sardinia, Italy

EFFICIENT MULTISCALE MODELING USING MACHINE LEARNING AND MODEL-ORDER REDUCTION SCHEMES

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ABSTRACT

Model-order reduction and artificial intelligence are gaining an increasing role in modern computational technologies, where they are often combined with conventional approaches such as the Finite Element (FE) method. Multiscale simulations relying on computational homogenization are almost a perfect candidate for model-order reduction and machine learning. In those simulations, indeed, a so-called fine scale problem should be solved for each point of the coarse scale model. The fine scale problem involves a heterogeneous domain and boundary conditions provided by the coarse scale, while the coarse scale involves a homogeneous domain and constitutive relations provided by the fine scale. A great number of computations hence involve the same problem being solved with various inputs. While pure FE^2 algorithms solve all problems for each different input, this mini-symposium invites presentations demonstrating how redundancy can be exploited in various ways to reduce the computational cost of multiscale simulations.

Many approaches consist in generating data using the FE method for a few different inputs in order to build a Reduced Order Model (ROM) from this so-called training database. Multiscale simulations are then conducted using an FExROM approach. Promising results have been obtained using proper orthogonal decomposition, proper generalized decomposition or self-consistent clustering analysis (FExPOD, FExSCA, etc.), as well as machine learning (FExNN, deep learning, autoencoders, recurrent neural networks, etc.). Recently, alternative strategies relying on clustering to directly reduce the number of fine scale problems to solve have also been proposed.