

SCIENTIFIC MACHINE LEARNING FOR PDES IN COMPLEX GEOMETRIES

O. COLOMÉS^{*}, A. HEINLEIN[†], S. BADIA[‡] AND N. MUELLER⁷

^{*} Delft University of Technology
j.o.colomesgene@tudelft.nl

[†] Delft University of Technology
a.heinlein@tudelft.nl

[‡] Monash University
santiago.badia@monash.edu

⁷ Delft University of Technology
N.Mueller@tudelft.nl

ABSTRACT

This minisymposium explores recent developments in scientific machine learning methods for solving partial differential equation (PDE)-based problems on complex geometries and topologies. Classical numerical methods address these challenges using advanced meshing, spatial adaptivity, and embedded techniques; while highly effective, they often entail significant computational cost and numerical complexity.

Learning-based approaches, including neural operators and neural network surrogates, offer a promising alternative. Although they often avoid explicit meshing, geometric information must still be encoded and incorporated into the model and training process, posing challenges in representing geometry, enforcing boundary and coupling conditions, and capturing small-scale features. Moreover, surrogate models mapping from geometry to solution require suitable parameterizations of the domain, ranging from pixel or voxel representations to (signed) distance functions and latent embeddings. There is also growing interest in methods that operate directly on mesh-based representations, such as graph neural networks.

This minisymposium brings together researchers from machine learning, numerical analysis, and computational science to discuss architectures, training strategies, theoretical foundations, and applications. We are particularly interested in neural network-based discretization approaches (e.g., physics-informed neural networks), methods building on classical numerical bases, as well as neural operator and surrogate modeling architectures, with an emphasis on robust and scalable methods for PDEs in complex geometries.