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ADVANCING NEURAL OPERATORS FOR DIGITAL TWINS IN MATERIALS AND STRUCTURAL ENGINEERING

SHAHED REZAEI[*], SOMDATTA GOSWAMI[†],

MOSTAFA E. MOBASHER[††] AND MAYU MURAMATSU[†††]

[*] Access e.V., Aachen, Germany
s.rezaei@access-technology.de

[†] Civil and Systems Engineering, Johns Hopkins University, MD, USA
somdatta@jhu.edu

[††] Civil and Urban Engineering, New York University Abu Dhabi, United Arab Emirates
mostafa.mobasher@nyu.edu

[†††] Department of Mechanical Engineering, Keio University, Yokohama, Japan
muramatsu@mech.keio.ac.jp

ABSTRACT

Digital twins are emerging as a key paradigm in materials and structural engineering, enabling real-time prediction, monitoring, and optimization of complex physical systems. A central challenge is the development of surrogate models that are both computationally efficient and physically consistent while capturing high-dimensional and nonlinear behavior. Neural operators have recently gained attention as a powerful framework for learning mappings between function spaces and approximating solution operators of governing equations, making them well-suited for digital twin applications.

Despite their promise, several challenges remain, including handling multi-input parametric variability, extending to multiphysics settings, and ensuring temporal consistency through causality-aware formulations. Additional issues include spectral bias, limited data efficiency, and the need to systematically incorporate physical constraints.

This minisymposium invites contributions addressing these challenges through methodological advances and engineering applications. While the primary focus is on neural operators, contributions based on other deep learning approaches are also strongly encouraged to foster a broader discussion on the capabilities and limitations of different methodologies for digital twin modeling. Of particular interest are physics-informed and hybrid approaches that combine learning-based models with classical numerical methods.

Overall, the goal is to advance data-driven modeling strategies as enabling technologies for robust, efficient, and physics-consistent digital twins in materials and structural engineering.