SCIENTIFIC MACHINE LEARNING: ADVANCING DESIGN AND DIAGNOSTICS OF ENGINEERING SYSTEMS FOR GREEN FUTURE

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ABSTRACT

The design and health monitoring of efficient and sustainable engineering systems demand computational approaches capable of addressing the intricate interplay of complex dynamics, multiscale and multidisciplinary physical phenomena, limited and sparse data often expensive to acquire, and safety critical decisions under uncertainty. Scientific Machine Learning (SciML) offers advanced computational approaches bridging scientific computing and domain-specific knowledge to address those complex challenges [1-3]: (i) in design, SciML accelerates the design optimization and prototyping of complex multi-physics systems; (ii) in diagnostics, SciML provides robust tools for real-time monitoring, predictive maintenance, and fault detection of critical systems. This minisymposium will highlight recent advances in SciML methodologies tailored for design and diagnostics in science and engineering, including surrogate modeling and model reduction techniques, physics-informed deep learning, and Bayesian approaches to inverse problems. Additional topics will include methodologies for data assimilation, interpretable machine learning, multisource and multifidelity active learning methods, digital twins, and optimal experimental design, showcasing their role in addressing challenges in the design and diagnostics of engineering systems, and in broader sustainability-focused efforts in resource efficiency, waste reduction, and environmental impact mitigation.

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