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Progress and Perspectives of Physics-Informed Neural Networks for Tribological Applications with Multiphysics Awareness

A.Yu. Kokhanovskiy [1], L.M. Dorogin [2,3], X.A. Egorova [4], E.V. Antonov [2], D.A. Sinev [4]

[1] Faculty of Physics, ITMO University, Kronverkskiy pr., 49, lit. A, St. Petersburg, 197101, Russia
[2] Institute of Advanced Data Transfer Systems, ITMO University, Kronverkskiy pr., 49, lit. A, St. Petersburg, 197101, Russia
[3] Department of Molecules and Materials, University of Twente, Enschede, The Netherlands
[4] Institute of Laser Technologies, ITMO University, Kronverkskiy pr., 49, lit. A, St. Petersburg, 197101, Russia

Received: April 08, 2025 Corresponding author: E.V. Antonov

Abstract. Recent advancements in the field of physics-informed neural networks (PINNs) hold great potential for solving the tribology-related problems, and areas for their applications are systematically reviewed in this article. The tribological applications are viewed as fundamentally dependent on the variety of multiphysics phenomena, which must be taken into account when developing PINNs. Materials data, topology and surface roughness, and analytical tribometry data can be used as multiphysics input for the PINNs specialized in solving friction, lubrication, wear, wetting, heat transfer, structural and phase transitions, chemical reactions, cracking, and fretting problems. Creating multi-PINNs that synthesize the individual tribology phenomena into the complex multiagent approach is viewed as a practically important and challenging issue that is yet to be addressed.

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