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PHYSICS/DNS-INFORMED DNN SURROGATES OF TURBULENT THERMAL CONVECTION

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The motivation of this work stems from the limited understanding of the physical mechanisms responsible for the heat transfer enhancement in turbulent convection over rough geometry. Indeed, in natural convection, strong dynamic interactions between a large spatial/time scale range from mean wind to small-scale plumes remain difficult to investigate based on partial data acquisition from expensive direct numerical simulations (DNS) [1] or the spatially limited measurements of experimental set-ups. Moreover, the development of data-driven surrogate models for the prediction and compression of such complex fluid phenomena, in place of more standard numerical simulations may help when many query and/or real-time simulations are required, for instance in order to perform signal processing and analysis, uncertainty quantification, data assimilation or control [2]. In this study, we make the choice to rely on deep neural networks (DNN). The approach retained is the one of training a DNN by leveraging some underlying physical laws (PDE) of the system. A natural approach is to incorporate (some of) the governing partial differential equations of the physical model (e.g. mass/momentum/energy conservation) at the core of the DNN, i.e. in the loss/likelihood functions, [3, 4]. We propose to investigate how this additional information effectively regularizes the minimization procedure in the training of DNN, and allows the recovery of various hidden flow variables when the training is performed with partial data. More specifically, we will report on the influence of the choice of the training domain for data acquisition as well as for the enforcement of the PDE, in relation to the problem geometry and initial/boundary conditions. Finally, we will put in perspective the future use of experimental data in place of DNS data.

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