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Editorial

Topical issue on quantitative AI in complex fluids and complex flows: challenges and benchmarks

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This topical issue of The European Physical Journal E brings together several papers at the interface of several disciplines dealing with the interpretability, superiority and usability of artificial intelligence algorithms as tools for both theoretical and applied fluid mechanics problems with applications in several fields such as engineering, geophysics and biophysics. The collection addresses open problems, challenges, and benchmarks for data-driven/equation-informed tools for data assimilation, (subgrid-scale) modeling, classification, and (optimal) control of Eulerian and Lagrangian problems in complex flows. The goal is to move from proof-of-concept to quantitative benchmarks and grand challenges, including scaling of algorithms and complexity of datasets. A typical challenge in data analysis of complex systems is to extract hidden information from partial observations; in this issue, these aspects have been addressed to infer unknown physical parameters in the context of turbulence on a rotating frame using a deep convolutional neural network [5], to identify and track the position of moving bubbles in microfluidics using a state-of-the-art object detector algorithm [9], and to infer relative permeability curves from sparse saturation data using an ensemble Kalman method [18]. The problem of designing control strategies is another aspect where AI is getting increasing attention; in this topical issue, machine learning and genetic algorithm have been investigated in air jets to control rotating stall in axial compressors [11], while deep reinforcement learning algorithms have been designed and benchmarked to reduce drag in turbulent channel flows [12]. Similarly, a typical data assimilation problem is to infer missing data from partial observations of Euler fields. Four papers have directly considered different machine learning approaches to tackle this problem. On the one hand, purely data-driven generative adversarial networks (GANs) have been designed to infer one velocity component from the measurement of the other two in the case of 3D turbulence under rotation, and show to outperform the results of standard approaches both in terms of pointwise and statistical reconstructions [14]. On the other hand, physics-informed neural networks have been investigated to reconstruct turbulent Rayleigh–Bénard flows using only temperature information [7] and to generate turbulent states satisfying given statistical conditions [2]. It has also been presented a new computational method for solving inverse problems in fluid mechanics, incorporating a multigrid technique into the Optimizing a DIscrete Loss (ODIL) framework [13]. Several papers are focused on solving optimal navigation tasks. Q-learning was employed so that an active particle could learn to navigate on the fastest path toward a target while experiencing external forces given by two different flow fields, a potential well and a uniform Poiseuille flow [17]. A multi-objective reinforcement learning (RL) approach was shown superior to heuristic strategies in optimizing the multi-objective goal of minimizing both the dispersion rate and the control cost of active particles [6]. RL has also been used to find optimal navigation policies for thin, deformable microswimmers moving in viscous fluids by propagating a sinusoidal wave along their body [10], and to optimize the control of a kite towing a vehicle over long distances by providing a simple list of maneuvering instructions able to maximize the power extraction from the wind [16]. Deep reinforcement learning was used to generate policies for sniffing robots designed to mimic the task of insects searching for an odor source in a turbulent environment [15]. Regarding turbulent modeling in [4], the idea of curriculum learning has been exploited to design ad hoc protocols for structuring the training data set to improve the quality of long-term model predictions. In [8], a deep learning approach was implemented to learn from data collision operators for the Lattice Boltzmann method, demonstrating the possibility of embedding physical properties, such as conservation laws and symmetries, directly into the deep learning model and proving its superiority over physics-agnostic models. Other two papers have con-

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tributed in this direction. One has studied a hybrid data-driven/finite volume method for 2D and 3D thermal convective flows, showing the success of a machine learning model in reducing the errors in the prediction of the heat flux [1], and the other discusses the results and the open challenges in the application of neural network-based methods to improve the accuracy of large eddy simulations of incompressible wall-bounded turbulent flows [3]. The diversity of AI approaches and applications presented in these papers provides a broad perspective on AI challenges and future advances in the fluid dynamics landscape. This highlights an active research area with great potential and rich of interdisciplinary collaborations, fostering exciting prospects and opening new avenues for cross-fertilization between different fields. To overcome some of today's challenges related to the need for quantitative AI, driven by several critical factors such as validation and generalization benchmarks, it is highly desirable in the future to have similar combined actions between groups, also driven in the future by well-formulated challenges and standardized open access databases, such as Smart-Turb (https://smart-turb.roma2.infn.it) is a first example.

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