

Editorial

Advancing Fluid Mechanics with Artificial Intelligence and Machine Learning

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Fluid mechanics research is currently undergoing a significant transformation, driven by the integration of advanced computational intelligence. While theory, experiment, and high-fidelity simulation remain essential, artificial intelligence (AI) and machine learning (ML) now provide a powerful set of tools for extracting patterns and building models from large datasets. What was, only a few years ago, a novel trend has rapidly matured into an essential, and nearly standardized, component of the modern research toolkit [1]. These techniques have opened the way to new approaches to solve the most persistent and complex problems in fluid dynamics, such as turbulence modeling, flow control, drag reduction, combustion instability, and aerodynamic optimization [2–5]. Nonetheless, the current focus on data presents a significant challenge: scaling analysis methods to effectively process the massive volumes of information from high-fidelity simulations and advanced experimental techniques. The central theme of this Special Issue is, therefore, to achieve a new synthesis: to join advanced data science, AI, and ML techniques with core fluid mechanics problems. In all papers included, AI/ML methods are not just applied, but they are integrated in a way that explains and incorporates the underlying physical laws.

Four review articles set the basis of AI/ML connection to fluid dynamics. It is a fact that AI/ML methods need to be adjusted to fit specific problems, and it's essential to test their accuracy and understand their limitations. The key is to go beyond simple predictions and help us understand why things happen. In the review of Drikakis and Sofos [6], the regions where AI can aid fluid dynamics have been pointed out. A key research focus should be exploring how ML can speed up numerical simulations while also investigating its accuracy limits in both experiments and simulations. It's also vital to figure out how to apply ML methods effectively in both massive datasets scenarios and data-scarce situations. Beyond just using these tools, a better theoretical understanding of how ML works needs to be established. In Aly [7], an in-depth analysis of recent advancements in integrating AI/ML with computational fluid dynamics (CFD) is provided. One of the most impactful contributions of ML to CFD is the drastic reduction in computational time. Increasing accuracy in turbulence modeling, which remains a critical challenge in CFD, particularly for RANS simulations, is another point. The development of data-driven and physics-driven surrogate models are also presented, aiming at solving complex fluid dynamics or uncovering simplified representations of physical processes.

In cases where obtaining complete spatiotemporal datasets is difficult, particularly when modeling turbulent flows, physics-informed neural networks (PINNs) are employed to address this challenge. In El Hassan et al. [8], various fluid mechanics applications with sparse data are examined, and PINNs have been found to be accurate in resolving the implied flow fields. The authors conclude that the future of fluid mechanics partly depends on how data and physics-driven approaches will be embedded on current theoretical and computational frameworks. On the other hand, the choice of an AI/ML framework is not always the best choice. There are complex cases like separated turbulent flows where current



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joint ML/Reynolds-Averaged Navier-Stokes (RANS) methods are not yet mature enough to outperform established simulation techniques, especially for extrapolation. In Heinz [9] the alternative of minimal error continuous eddy simulation (CES) methods is suggested, to properly account for causal relationships inherent to separated turbulent flows.

Starting from applications close to the atomic scale, a ML model capable of reproducing and predicting the properties of ionic liquids is presented [10]. Along with interpretable, explainable and generalizable symbolic expressions derived with Symbolic Regression (SR) methods [11,12], the electrical conductivity of ionic liquids is given as an analytical equation for the first time, overcoming the high cost and computational demands of experiments and molecular simulations. In another application the viscosity and surface tension, which characterize the rheological properties of liquids, are employed to calculate the Ohnesorge number from dispensed droplet images [13]. Seven different convolutional neural network (CNNs) architectures are constructed and employed to extract information from spatiotemporal data, reaching an accuracy of nearly 95%. A further application in rheology involved predicting the viscosity of a BN-diamond/thermal oil hybrid nanofluid with four traditional "black-box" ML algorithms (Random Forest, Gradient Boost, Gaussian Regression, and Artificial Neural Network), with the ensemble tree-based Gradient Boost achieving the best performance [14].

As we move towards the macroscale, PINNs are widely used in fluid dynamics research during the past years to predict flow fields, especially in high-Reynolds number flows where turbulence dominates. Even when trained with low-resolution RANS equations, sufficient models emerge and the results are comparable to high-resolution DNS data [15]. By employing a generative adversarial network (GAN) and combining it with physics-informed constraints inside the loss function, a high-performing super-resolution framework is suggested in the paper by Ward [16], resulting in superior performance in both accuracy and computational efficiency for 3D turbulence cases. From an algorithmic point of view, it has been also shown that fully connected neural networks (FCNNs), whose loss function consists of both data and physics constraints, perform better compared to data- or physics-only models [17]. Moreover, the PINNs' potential for real-world applications is highlighted through an ocean engineering context [18]. The hydrodynamic nonlinear Schrödinger equation is embedded inside the loss function and works accurately even with limited data availability.

For application-specific research in hydraulic engineering, the work of Salemnia et al. [19] applies various ML algorithms to predict the dynamic pressure coefficients of vertical water jets, using data from controlled hydraulic laboratory experiments. With ML methods, it overcomes the limitations of traditional numerical models in complex turbulent flows and suggests more resilient hydraulic structure designs. In coastal engineering, ML is employed to guide breakwater design, predicting the value of the reflection coefficient and complementing other traditional methods. It is concluded that the reflective power of the underwater breakwater is increased analogous to its length, while wave attenuation reaches the maximum at shallow depths [20]. Machine learning is also used to replace the manual fine-tuning calibration required on pre-production motorcycles [21]. Trained on rolling bench data, the ML model (ANN or Random Forests) learns to accurately estimate air mass flow, a sensitive parameter crucial for torque and catalyst efficiency. This method successfully saves many days of calibration work without sacrificing accuracy, even when starting from a completely random (worst-case) calibration. Beyond that, to account for high emissions from gasoline direct injection engines during cold starts, another application employs ANNs to predict fuel spray behavior. The ANN successfully predicted detailed spray dynamics, including liquid penetration and width, with excellent accuracy [22]. Finally, an integrated AI/CFD framework with Deep NNs is constructed to forecast temperature and humidity values inside a ventilated room, while master control is

carried out by a digital twin [23]. CFD data are used for model training and control. The findings validate the effectiveness of AI-based digital twins for control applications, highlighting their potential to improve system autonomy, optimize performance, and increase operational efficiency, making them key technologies for modern control engineering.

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