Physics-informed data-driven URANS turbulence modelling for particle-laden jet flows with various Stokes numbers

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In this study, with the assistance of deep learning (DL), we present a framework for predicting turbulent eddy viscosity in unsteady Reynolds-averaged Navier–Stokes (URANS) simulations for particle-laden flows. A complete workflow is illustrated from the identification of input flow and particle quantities to the final prediction of the instantaneous flow velocities. The framework incorporates a deep neural network model, also known as multi-layer perceptrons (MLP), into the momentum equations of the Euler–Lagrangian gas–solid flow system. A data-driven, physics-informed DL approach is employed to predict the modelled turbulent eddy viscosities, which are formulated as functions of the instantaneous flow and particle quantities. In the training phase, such eddy viscosity functions are trained by the existing high-fidelity direct numerical simulation database. In the testing phase, they are then used to predict the instantaneous local eddy viscosity to update the closure term and to solve the URANS equations iteratively. That is to say, the DL prediction is performed every timestep in the URANS solver. The velocity and pressure fields of turbulence, as well as the particle motions, are solved iteratively until their residuals converge to the given tolerance within each timestep.

Assessments of the model are performed for round, turbulent particle-laden jet flows with various Stokes numbers to represent practical computational fluid dynamics applications. Here, the Stokes number characterises the ratio of the particle response time to the fluid response time of the flow system. For the URANS of such nonhomogeneous flows, the proper input flow features (i.e., the instantaneous flow quantities) and the effective form of the closure term (i.e., the turbulent eddy viscosity) are discussed to identify the suitable training input and target variables for the DL model. In such an identification process, the physical domain knowledge is considered to establish a proper regression system. The proposed DL–URANS model is found to provide enhanced capability in predicting the flow and particle quantities compared with the baseline URANS simulations. Finally, the *a posteriori* tests using different flow parameters and different classes of flows are performed to evaluate the robustness of the DL-URANS framework.

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