The 8th European Congress on Computational Methods in Applied Sciences and Engineering
ECCOMAS Congress 2022
5 – 9 June 2022, Oslo, Norway

Neural network-based filtered drag model for cohesive gas-particle flows

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Key Words: *Data-driven modelling, Multiphase flow, Cohesive particles, Machine Learning*

Simulations of industrial-scale gas-particle flows based on the filtered Two-Fluid model (fTFM) approach, and therefore with coarse grids, depend critically on constitutive models that account for the effects of inhomogeneous structures at the subgrid level [1]. Around this issue, an artificial neural network-based drag correction model was developed by Jiang et al. [2,3] for non-cohesive gas-particle systems.

The complexity of accounting for inhomogeneous structures increases when considering cohesive gas-particle flows [4]. Therefore, we aim to analyze the influence of cohesion on the drag force closure and integrate it into a machine learning-based drag correction concept. Prior studies [5] identified the sub-grid drift velocity as the crucial quantity for modeling the filtered drag coefficient and the drag model as a whole. Unfortunately, the drift velocity is unavailable in filtered simulations. To correctly reproduce mesoscale structures, and since the drift velocity is also computable, we start with detailed CFD-DEM (Computational Fluid Dynamics-Discrete Element Method) simulations and filter them with different filter sizes to emulate an fTFM simulation.

Based on these simulations, we create a dataset by varying the cohesion level from cohesionless to highly cohesive and changing the size of the systems using coarse-graining. We then subject the markers available in a basic fTFM simulation to systematic analysis considering their correlation with the target value, namely the drift velocity. With the identified markers we then create, train, and test neural network-based drag correction models. Finally, we demonstrate the accuracy of the developed models for drag correction for a wide range of cohesion levels and system sizes.

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