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Coupled RANS–LPT modelling of dilute, particle-laden flow in a duct with a 90° bend

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ABSTRACT

A dilute, particle-laden flow in a square duct with a 90° bend is modelled using a RANS approach, coupled to a second-moment turbulence closure, together with a Lagrangian particle tracking technique, with particle dispersion modelled using a stochastic approach that ensures turbulence anisotropy. Detailed predictions of mean and fluctuating fluid and particle velocities are validated through comparisons of predictions with experimental measurements made for gas–solid flows in a vertical-to-horizontal flow configuration. Reasonable agreement between predicted first and second moments and data is found for both phases, with the consistent application of anisotropic and three-dimensional modelling approaches resulting in predictions that compare favourably with those of other authors, and which provide fluctuating particle velocities in acceptable agreement with data.

1. Introduction

Particle-laden flows have numerous areas of application (Mohanarangam et al., 2008), and the transport of such flows requires detailed understanding to permit their accurate prediction. Two numerical approaches are generally used in modelling such flows, these being the Eulerian–Eulerian and Eulerian–Lagrangian approaches, with the choice between these two reference frameworks in essence being problem-dependent. The former approach treats both phases as interpenetrating and interacting continua, and the coupled governing equations are then solved for each phase giving the time dependent behaviour of the two phases (Mohanarangam et al., 2008; Tu and Fletcher, 1995). This approach is economical and convenient for implementing two- and four-way coupling between the fluid and particle phases. Its drawback is in the complexity associated with accommodating particle phase fluctuations, particle–wall collisions, certain boundary conditions and poly-dispersed particle sizes. The consideration of a particle size distribution, in particular, requires the solution of a set of equations for each size class considered, and hence the computational effort increases with the number of size classes. The Eulerian–Lagrangian approach differs in not considering the particle phase as a whole, but in tracking individual representative particles in the flow, with their trajectory simulated using Newton's second law of motion (Gouesbet and Berlemont, 1999; Mohanarangam et al., 2007). This method performs well in those areas, noted above, that represent drawbacks for the Eulerian–Eulerian approach, but has a significant problem itself associated with having to simulate large numbers of particle trajectories in order to generate statistically meaningful results. A more complete review of both approaches can be found in Crowe et al. (1996). Despite the pros and cons of both methods, the Eulerian–Lagrangian approach remains the most popular model for use in predicting dilute multiphase flows, particularly due to its ability to model the crossing trajectories of particles caused by particles moving on different paths to the carrier fluid (Chen, 1997). With increasing computer power, in terms of memory and computation speed, high performance Eulerian–Lagrangian models have become very useful and versatile tools for studying the dynamics of particle-laden flows precisely because they account for the discrete nature of the individual particles.

In the Eulerian–Lagrangian approach, while the particles transverse the flow domain they interact with their surroundings, and these interactions dictate the particle dynamics inside the particular geometry under consideration. Interactions with the surroundings are incorporated by modelling the external forces acting on the particles, as well as particle–wall and particle–particle interactions. These interactions are further complicated if the flow is bounded by concave and convex walls, as in the present case, which cause changes in the direction of flow. For dilute suspensions, which form the basis of this study, these interactions are largely dominated by inertial effects since particles of different sizes selectively interact with different scales of fluid motion (Grigoriadis and Kassinos, 2009). Inertial effects are caused by the reluctance of particles to follow exactly the fluid streamlines, which largely depends on the characteristic time scales between the two phases. The relative importance of the these time scales is usually expressed by the dimensionless Stokes number, defined as the ratio $St = \tau_p/\tau_f$, where

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τ_f is the characteristic time scale of the fluid phase and τ_p is the particle response time which describes the time that a particle needs to adjust to a change in the flow velocity. Particles with high Stokes numbers augment the inertial effect, with the influence of wall collisions becoming important when these particles are driven close to solid surfaces, with such collisions often dominating the motion of large particles. Small particles, with $\mathrm{St} \ll 1$, in the neighbourhood of a boundary layer diffuse towards the wall surface under the influence of turbulent eddies in the flow. Although these eddies dissipate as they approach the wall, the particles continue to travel towards the surface by the free flight mechanism due to their inertia. Thus, in low Stokes number flows, turbulent diffusion dominates wall collisions. However, if small particles by chance collide with a wall, the wall collision effect does not have a considerable influence on the particle motion if they continue to follow the mean fluid flow soon after the collision. When particles collide with a wall, the influence of wall roughness and particle shape also come into play, affecting the particle rebound velocity and the drag force thereby influencing the particle motion. The "virtual wall" model (Tsuji et al., 1987; Sommerfeld, 1992) can be employed to simulate the influence of wall roughness, as well as treating non-spherical particle–wall collisions (Sommerfeld and Huber, 1999), by redirecting the particle momentum randomly each time a particle collides with a wall (Tsuji et al., 1987).

Large particle rotational velocities lead to a spin lift force arising from the deformation of the flow field around a particle that causes a pressure difference across the particle. Since particles can acquire high rotational velocities after wall collisions, this effect can be of importance in the near wall region (Sommerfeld, 2003). Changes in the direction of a flow, as in a bend, generate velocity and pressure gradients with strong shear layers close to the geometry boundaries, with large gradients inducing a slip-shear force on the particles. Hence, lift forces will occur in particulate flows in curved ducts and need to be accommodated in simulating the particle dispersion. Details of the importance of all external forces acting on particles on their dispersion, with respect to particle size and the density ratio between the two phases, can be found elsewhere (Armenio and Fiorotto, 2001).

To solve the particle equation of motion, the instantaneous fluid velocities in all directions at the particle position are required. Hence, the instantaneous velocities seen by the particles and their effect on the particles' dispersion and distribution need to be quantified. In the Reynolds-averaged Navier–Stokes (RANS) modelling framework, the instantaneous fluid velocities are decomposed into a mean velocity $\bar{u}$, and a fluctuating component u'. The mean part is then obtained directly from the time-averaged Eulerian solution (deterministic), whereas the fluctuating part must be obtained separately through stochastic modelling.

Reliable experimental data are needed to validate numerical models, with the Kliafas and Holt (1987) data set often used in the validation of predictions of particle-laden two-phase flows in 90° duct bends. Some of the studies that used these data for validation purpose are those of Tu and co-workers (Tu and Fletcher, 1995; Mohanarangam et al., 2007; Mohanarangam et al., 2008; Tian et al., 2008) who applied the renormalization group (RNG) theory-based k–ε and standard k–ε models in the commercial CFD code FLUENT in their simulations. The authors used both Eulerian–Eulerian (Tu and Fletcher, 1995; Mohanarangam et al., 2008) and Eulerian–Lagrangian (Tian et al., 2008) approaches, and compared both approaches (Mohanarangam et al., 2007) in terms of their ability to predict such gas–solid flows. Comparison of predicted gas mean velocities and the root-mean-square (rms) of velocity fluctuations in the streamwise direction with the Kliafas and Holt (1987) experimental measurements for $\mathrm{Re} = 3.47 \times 10^5$ showed good agreement. The Eulerian–Eulerian approach showed superior agreement with data for the rms of velocity fluctuations of the particle phase, while the Eulerian–Lagrangian method gave more detailed information about the particle behaviour. There were some discrepancies between predictions and data for the rms of velocity fluctuations around the bend region, with the authors observing an under-prediction of the gas turbulence intensity in the boundary layers on both the inner and outer walls of the

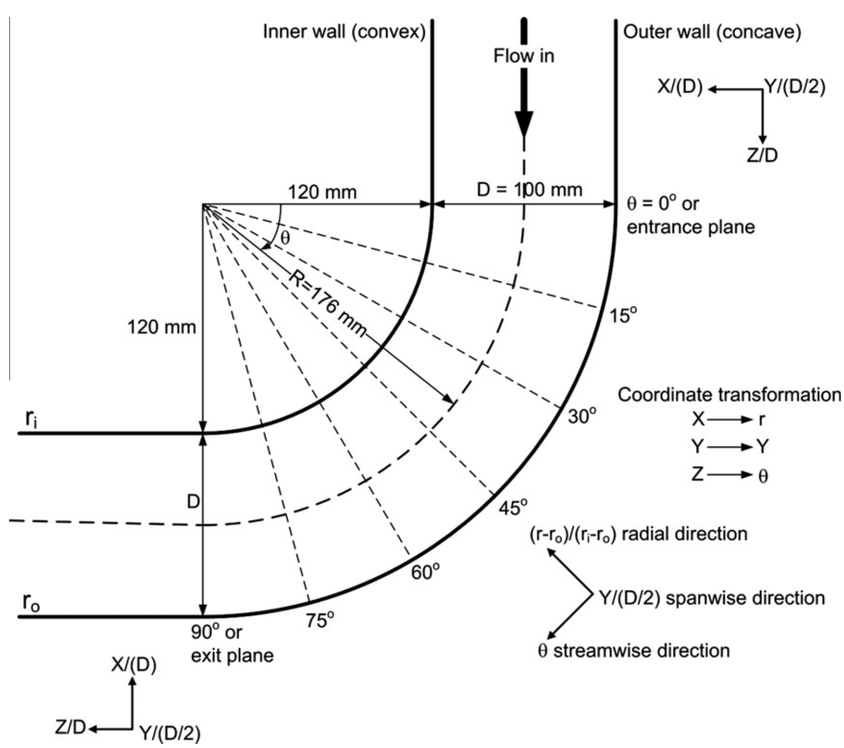

Fig. 1. Schematic representation of computational domain and coordinate system.