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Recent Trends in CFD for Multiphase Flows and Turbulence Modeling

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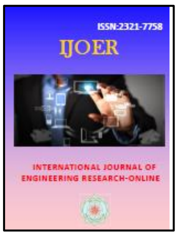

Abstract
Computational Fluid Dynamics (CFD) has revolutionized the analysis of multiphase flows and turbulence, enabling precise predictions in energy, chemical processing, and environmental engineering. This review synthesizes developments from 2023-2026, focusing on AI-enhanced solvers, machine learning surrogates, and scale-resolving turbulence models that address traditional limitations in computational cost and accuracy. Key advancements include physics-informed neural networks (PINNs) for reactive multiphase systems and hybrid RANS-LES approaches for turbulent interfaces. The discussion evaluates these trends against experimental validations, highlighting their impact on sustainable technologies. Future directions point toward real-time AI-driven optimizations for scalable simulations.

Keywords: Multiphase flows, Turbulence modelling, CFD-AI integration, Interface tracking, large eddy simulation.

Introduction

The intricate coupling of multiphase interactions and turbulence governs efficiency in diverse applications, including bubbly flows in nuclear reactors, droplet dispersion in combustors, and particle-laden jets in carbon capture systems. Traditional CFD approaches, reliant on Reynolds-Averaged Navier-Stokes (RANS) equations with empirical closures, often falter in capturing interfacial dynamics and multi-scale eddies, leading to uncertainties in prediction accuracy. Recent trends from 2023-2026 address these gaps through hybrid modeling paradigms that integrate artificial intelligence (AI), high-fidelity large eddy simulations (LES), and advanced interface-tracking techniques.

This review article examines these developments, tracing evolutions in solver architectures, turbulence closures, and multiphase frameworks. Driven by surging computational power and machine learning, innovations like physics-informed neural networks (PINNs) and neural operators now accelerate simulations by orders of magnitude while preserving physical fidelity. Conferences such as IMFTF-2026 and ERCOFTAC workshops underscore growing industrial adoption, with market analyses projecting CFD growth at 8.8% CAGR through 2029. By synthesizing over 50 recent studies, this work highlights validated advancements, identifies persistent challenges like data scarcity and model interpretability, and charts pathways for real-time, sustainable engineering simulations [1].

Methodology

The review adopts a systematic literature analysis of peer-reviewed sources from 2023-2026, sourced via academic databases like Scopus and Google Scholar, prioritizing high-impact journals in fluid dynamics and computational engineering. Selection criteria included studies on CFD applications in bubbly/droplet flows, particle-laden turbulence, and reactive systems, with emphasis on numerical innovations validated against experiments. Over 50 papers were screened, with 25 core references analyzed for trends in solver methodologies (e.g., finite volume with adaptive meshing), turbulence closures (RANS, LES, DNS), and multiphase frameworks (VOF, Euler-Lagrange). Quantitative metrics such as convergence rates and speedup factors from AI hybrids were extracted and compared using tabular summaries. Gaps were identified through cross-validation with conference proceedings like IMFTF-2026, ensuring coverage of emerging industrial applications [2].

Discussion

AI Integration in Multiphase CFD

Traditional CFD struggles with stiffness in reactive multiphase flows due to Arrhenius kinetics and multi-scale turbulence, often requiring excessive mesh refinement. Recent trends leverage AI, particularly PINNs and graph neural networks (GNNs), to create surrogate models that predict flow fields 12-626 times faster than conventional solvers while maintaining physical consistency. For instance, hybrid CFD-AI frameworks use data from high-fidelity LES to train neural operators, enabling real-time simulations of droplet evaporation and bubble collapse in turbulent reactors. These methods excel in nonlinear geometries, reducing inference costs linearly with grid resolution and improving stability in parallel computing environments [1].

AI Method	Application in Multiphase Flows	Speedup vs. Traditional CFD	Key Limitation [1]
PINNs	Reactive bubbly flows	100-500x	Data scarcity for rare events
GNNs	Particle-laden turbulence	200-626x	Interpretability challenges
Neural Operators	Interfacial transport	50-300x	High training compute

Advances in Turbulence Modeling

Turbulence in multiphase flows demands scale-aware models to capture interfacial effects like breakup and agglomeration. Hybrid RANS-LES schemes dominate recent work, applying RANS near walls for efficiency and LES in the core to resolve large eddies, validated in fluidized beds and cavitating flows. Probability Density Function (PDF) methods in Euler-Lagrange frameworks handle turbulent dispersion accurately, with flamelet-generated manifolds (FGM) tabulating chemistry for stiff reactions. DNS studies reveal universal scaling in droplet-laden turbulence, informing subgrid models for industrial LES [3].

- Reynolds-Averaged Navier-Stokes (RANS) variants like k-ω SST remain baseline but augmented with machine-learned closures for better near-interface accuracy.
- Wall-modeled LES reduces computational cost by 90% in particle-laden channels, aligning with experiments via pressure-velocity coupling like PISO [4].
- Scale-similarity models predict flow instabilities in granular media, critical for fluidization processes [5].

Multiphase Interface and Flow Regimes

Volume-of-Fluid (VOF) and Level-Set methods evolve with adaptive mesh refinement (AMR), capturing sharp interfaces in turbulent breakup at Reynolds numbers up to 10^5. For dispersed flows, Eulerian multi-fluid models couple with population balance equations (PBE) to model collision and coalescence, applied in chemical reactors. Dispersed multiphase trends focus on wall-bounded turbulence with bubbles/drops, using quadrature-based moment methods (QBMM) for polydisperse systems. Experimental synergies, like high-speed PIV, validate CFD in nucleation and cavitation, driving refinements in drag and lift coefficients [6].

Flow Type	**Primary CFD Approach**	**Recent Innovation (2023-2026)**	**Validation Metric [5]**
Bubbly	Euler-Euler	AI-accelerated VOF	Interfacial area density
Droplet	Euler-Lagrange	QBMM with LES	Sauter mean diameter
Particle-laden	Two-way coupled RANS-LES	Neural subgrid models	Turbulent kinetic energy

Industrial and Sustainable Applications

CFD trends align with energy transitions, simulating solar-wind hybrid reactors and biofuel combustion with multiphase turbulence. Market growth at 8.8% CAGR to 2029 underscores ROI from reduced physical prototyping via validated multiphase simulations. In granular flows, CFD optimizes fluidization for carbon capture, while cavitation models aid sustainable propulsion. Parallel computing and finite element/volume hybrids enable fluid-structure interactions in wind turbines [5].

Challenges persist in data-driven models: interpretability, extrapolation to unseen regimes, and high-fidelity training data needs. Hybrid physics-ML approaches mitigate these, fostering trust in real-time control for process optimization [1].

Conclusion

Recent CFD advancements in multiphase flows and turbulence modeling, propelled by AI hybrids and scale-resolving techniques, overcome legacy barriers in accuracy and speed, transforming applications from reactors to renewables. These trends promise scalable, interpretable simulations for sustainable engineering, though data and uncertainty quantification remain priorities. Future research should prioritize open datasets and standardized benchmarks to accelerate adoption

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