Research Plan (Konduru Rakesh Teja)

Plain-Language Summary

Understanding and predicting turbulence in urban regions requires high-resolution numerical modeling, particularly through Large Eddy Simulation (LES). A direct LES is computationally expensive, for instance, we used 50,000 cores on Fugaku supercomputer for ideal 2 meter urban LES, making real-time urban turbulence forecasting challenging. This LES provides high-resolution turbulence but requires subgrid-scale (SGS) closure models, introducing uncertainties. This study develops a lower-order, ML-based turbulence emulator "ML-Turb" for urban region trained on ultra-high-resolution LES data from the Fugaku supercomputer. The novelty lies in leveraging Empirical Mode Decomposition (EMD) with deep neural networks (DNNs) to enhance turbulence emulation and reduce dependancy on closure assumptions, improving computational efficiency while maintaining accuracy. The research integrates fundamental fluid dynamics, urban boundary layer theories, data-driven modeling techniques, and mathematical concepts to urban-induced turbulence (UIT) and improve ML-based turbulence predictions.

Objectives

Theme A: To develop a mathematical framework for the lower-order data-driven ML-based turbulence emulator "ML-Turb" for urban region.

Theme B: "ML-Turb" trained using urban region data from CUBE LES solver computed on Fugaku supercomputing. Demonstrate ML-Turb performance in simulating urban turbulence against CUBE LES solver.

Theme C: Develop a protoype of real urban turbulence by using ML-Turb for realitime urban turbulence prediction over Osaka region

Purpose

The increasing demand for accurate urban weather forecasting necessitates a deeper understanding of turbulence generation, dissipation, and transport mechanisms. LES offers an advanced tool to resolve these turbulent structures at high fidelity, but its high computational cost limits its practical application in operational forecasting and real-time decision-making.

Machine learning (ML) has revolutionized various fields by identifying complex patterns in high-dimensional datasets. However, applying ML to turbulence modeling is challenging due to its multi-scale nature and the need for accurate closure assumptions. Traditional turbulence models rely on empirical closures, while ML-based models must learn turbulence physics while ensuring generalizability.

LES, based on the Navier-Stokes (NS) equations, resolves large-scale turbulent motions while modeling subgrid-scale (SGS) turbulence through closure models, introducing uncertainties. These closure assumptions impact turbulence predictions, especially in urban regions with complex flow structures. The Navier-Stokes equations governing incompressible flow are given by:

$$\frac{\partial u}{\partial t} + u \cdot \nabla u = -\frac{1}{\rho}\nabla p + \vartheta \nabla^2 u + f \, ; \nabla \cdot u = 0$$

where u is the velocity field, p is pressure, ρ is density, ϑ is kinematic viscosity, and f represents external forces. In LES, the velocity field is filtered into resolved and subgrid components, requiring a closure model for the SGS stress tensor.

This study employs a data-driven approach, leveraging ultra-high-resolution LES simulations from the Fugaku supercomputer to train deep neural networks (DNNs). By incorporating Empirical Mode Decomposition (EMD), the ML model extracts turbulence dynamics across multiple scales, addressing closure challenges and improving accuracy.

The ML-based lower-order emulator developed in this study reduces computational costs while preserving turbulence physics, improving urban weather forecasting, refining turbulence parameterizations in numerical weather prediction models, and supporting sustainable urban development through faster, high-fidelity urban flow predictions.