Proceedings of the Canadian Society for Mechanical Engineering International Congress
32nd Annual Conference of the Computational Fluid Dynamics Society of Canada
Canadian Society of Rheology Symposium
CSME/CFDSC/CSR 2025
May 25–28, 2025, Montréal, Québec, Canada

Generalizable Deep Learning for Rapid Urban Wind Field Prediction Trained on Only 24 CFD Simulations

Shaoxiang Qin[1,2], Dongxue Zhan[1], Ahmed Marey[1], Theodore Potsis[1], Liangzhu (Leon) Wang[1*]

[1]Department of Building, Civil and Environmental Engineering, Centre for Zero Energy Building Studies, Concordia University, Montreal, Canada
[2]School of Computer Science, McGill University, Montreal, Canada
[*]leon.wang@concordia.ca

Abstract

Predicting wind behavior in urban environments is essential for multiple applications, including protecting human health, enhancing comfort, refining city planning, and optimizing path planning for urban air mobility. In these settings, forecasting wind, both its average speed and its temperature, is particularly challenging due to the complex layout of buildings. The varying distribution of buildings and narrow streets leads to intricate turbulence patterns and considerable variability in wind flow. Although traditional computational fluid dynamics (CFD) models are capable of capturing these complex interactions, their high computational demands render them impractical for real-time applications or for the iterative processes often required during realistic applications.

In response to these challenges, deep learning techniques have emerged as a promising alternative, offering the potential to deliver faster approximations of CFD results. However, in urban settings with complex geometric boundary conditions, these models often require large and varied datasets that encompass different building geometries to achieve reliable generalization. Developing a sufficiently large dataset requires considerable time and computational resources, which can be impractical for real-world applications.

This study introduces a novel machine learning method that predicts urban wind, including both average velocities and temperature, based solely on the geometrical configurations of city structures. The core of our method involves two main components: a multi-directional distance feature (MDDF) and a localized training strategy. MDDF encodes the urban layout by precomputing distance features that efficiently capture the spatial distribution and obstructions caused by buildings. This feature then serves as the input for the Localized Fourier Neural Operator (Local-FNO) model, which is designed to operate on small, three-dimensional patches throughout the simulation domain. This localized strategy enhances data efficiency, allowing the model to generalize effectively even with a limited number of training cases. It also introduces a high degree of flexibility and the potential for parallel processing. We perform transient CFD simulations and calculate the mean velocity and temperature after the flow field has fully developed. The boundary conditions of wind and temperature are fixed. Trained with just 24 CFD simulations, our method reliably estimates the 3D mean wind flow and temperature in previously unseen city configurations within 30 seconds, whereas a CFD simulation typically takes over 8 hours. Quantitatively, our model achieves a mean error of less than 0.5 m/s and 0.5 °C and maintains a correlation coefficient exceeding 0.9, demonstrating both precision and robustness in its predictions.