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Deep Learning to aid CFD simulations in Built Environment

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CFD in the built environment

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Deep learning to replace, improve, or aid CFD analysis in built environment applications: A review

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ABSTRACT

Fast and accurate airflow simulations in the built environment are critical to provide acceptable thermal comfort and air quality to the occupants. Computational Fluid Dynamics (CFD) offers detailed analysis on airflow motion, heat transfer, and contaminant transport in indoor environment, as well as wind flow and pollution dispersion around buildings in urban environments. However, CFD still faces many challenges mainly in terms of computational expensiveness and accuracy. With the increasing availability of large amount of data, data driven models are starting to be investigated to either replace, improve, or aid CFD simulations. More specifically, the abilities of deep learning and Artificial Neural Networks (ANN) as universal non-linear approximator, handling of high dimensionality fields, and computational inexpensiveness are very appealing. In built environment research, deep learning applications to airflow simulations shows the ANN as surrogate, replacement for expensive CFD analysis. Surrogate modeling enables fast or even real-time predictions, but usually at a cost of a degraded accuracy. The objective of this work is to critically review deep learning interactions with fluid mechanics simulations in general, to propose and inform about different techniques other than surrogate modeling for built environment applications. The literature review shows that ANNs can enhance the turbulence model in various way for coupled CFD simulations of higher accuracy, improve the efficiency of Proper Orthogonal Decomposition (POD) methods, leverage crucial physical properties and information with physics informed deep learning modeling, and even unlock new advanced methods for flow analysis such as super-resolution techniques. These promising methods are largely yet to be explored in the built environment scene. Unavoidably, deep learning models also presents challenges such as the availability of consistent large flow databases, the extrapolation task problem, and over-fitting, etc.

1. Introduction

The study and control of the airflow in the built environment is of great importance since it directly affects human daily life primarily in terms of health, comfort, and productivity. Now more than ever, the urban environment [1,2] and the indoor environment [3,4] are facing challenges in providing acceptable air quality and thermal comfort due to increasing pollution and climate change. Fast and accurate airflow information is therefore desirable when it comes to built environment applications of inverse design, system control, evaluation, and management. Computational Fluid Dynamics (CFD) is a useful tool that enables detailed predictions through numerically solving the Navier–Stokes (N–S) equations. Through the years, CFD has been widely and consistently used in the indoor environment to simulate turbulent airflow [5], heat transfer [6], and contaminant transport [7], as well in the urban environment to simulate wind flow around buildings [8] or at pedestrian level [9] and tracking pollutants [10]. However, CFD still faces many challenges mainly in terms of computational expensiveness and accuracy.

In realistic turbulent flow field cases, the N–S equations cannot be solved analytically, but numerically with space and time discretization. In order to fully capture the flow phenomena, all different scales of turbulence have to be resolved. This CFD approach is called Direct Numerical Simulation (DNS) [11]. Although DNS is conceptually simple, it is extremely computationally expensive and still infeasible on numerous applications. The Large Eddy Simulation (LES) [12] is another method that resolves the large three-dimensional unsteady turbulent motions directly and model the small-scale ones. This approach is justified by the universal shape and isotropy of the small-scale turbulence, but mainly applicable for external flow over large bodies where the boundary layer is of less importance. Although the computational effort compared to DNS is reduced, LES is still expensive and out of reach for

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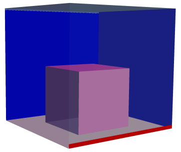
- CFD simulate airflow with great details, but there are **uncertainties** (turbulence models) and it is **not fast** enough.
- **Literature review** shows that in the built environment, deep learning is only used as surrogate modeling for faster prediction [1]
- Deep learning can **aid** fluid simulations instead of just replacing them.

[1] Calzolari, Giovanni, and Wei Liu. "Deep learning to replace, improve, or aid CFD analysis in built environment applications: A review." *Building and Environment* 206 (2021): 108315.

Coupled Framework

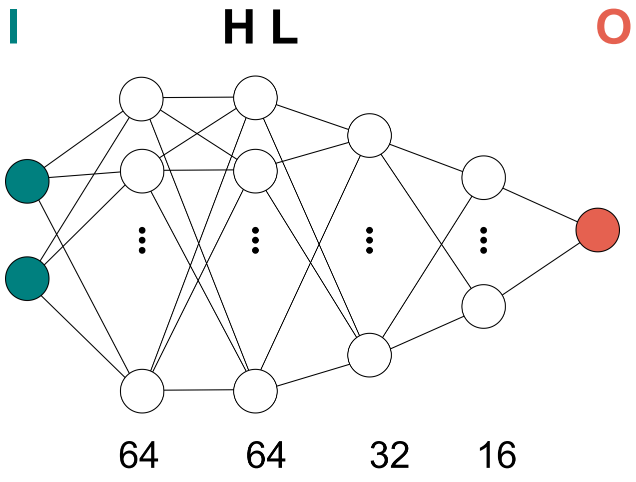
- We develop a **coupled CFD – deep learning framework** where we substitute only the turbulence model of CFD with a MLP



Run CFD simulation and gather data

Train MLP in Tensorflow

Implement the MLP on OpenFOAM and create the coupled framework

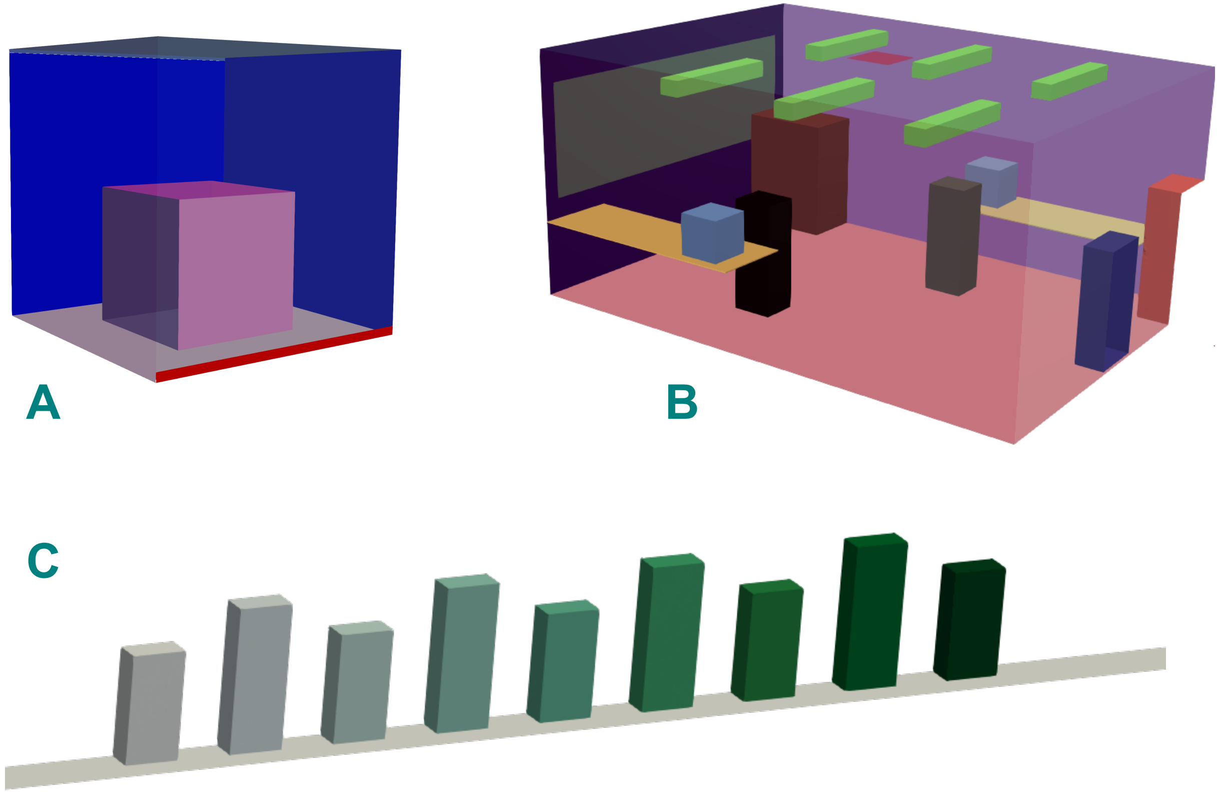


Flow Fields from literature

A. **Room** simulation mixed convection indoor airflow [2]. Data used to **train** the MLP.

B. **Office** simulation with displacement ventilation [3].

C. **Building array** simulation outdoor airflow [4].



[2] Wang, Miao, and Qingyan Chen. "Assessment of various turbulence models for transitional flows in an enclosed environment (RP-1271)." Hvac&r Research 15.6 (2009): 1099-1119.

[3] Yuan, Xiaoxiong, et al. "Measurements and computations of room airflow with displacement ventilation." Ashrae Transactions 105 (1999): 340.

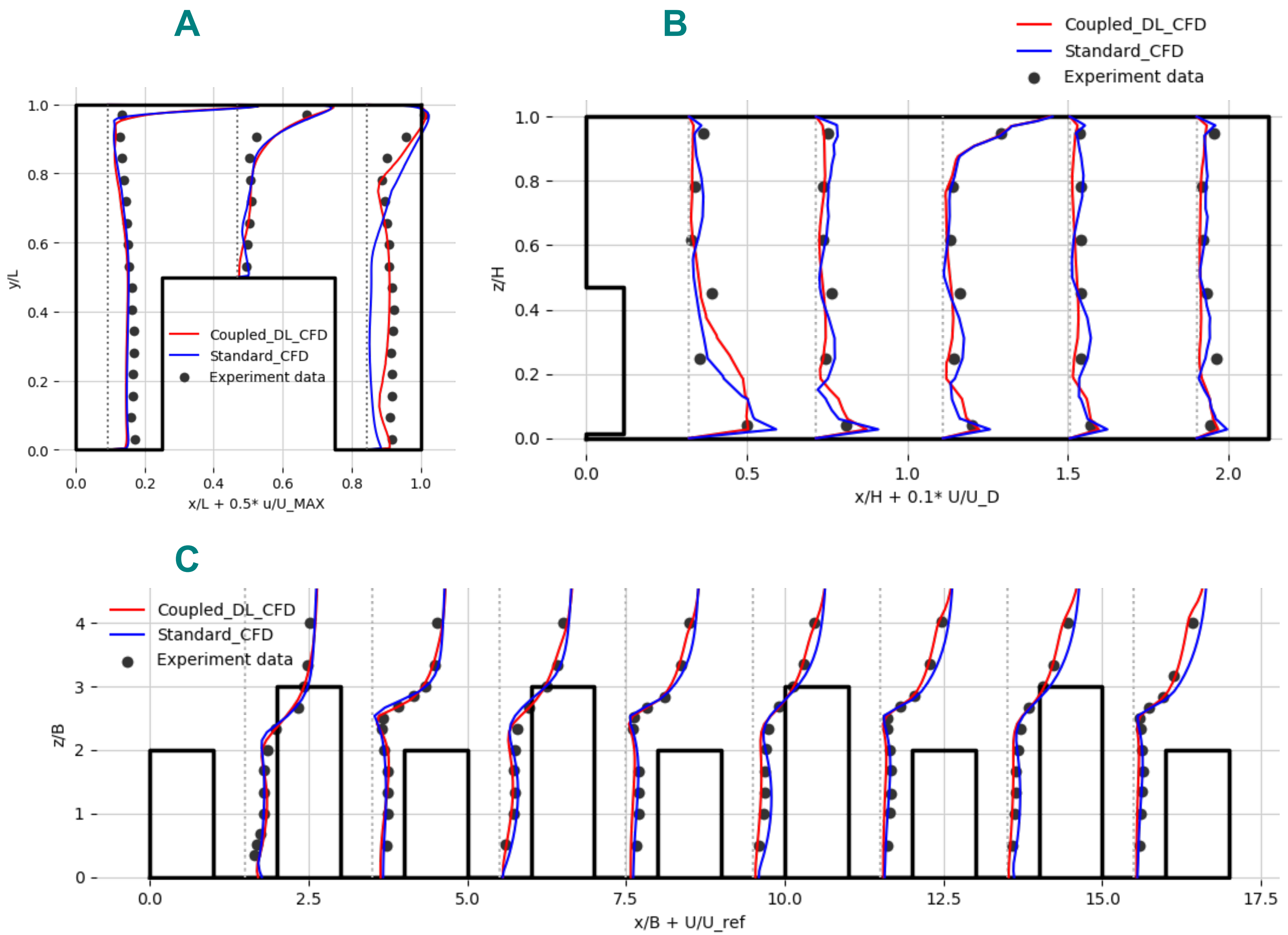
[4] Hang, Jian, et al. "The influence of building height variability on pollutant dispersion and pedestrian ventilation in idealized high-rise urban areas." *Building and Environment* 56 (2012): 346-360.

Compared to standard CFD simulation using RNG k-ε model the new coupled framework is:

A. **14.5 % faster***

B. **16.7 % faster***

C. **17.2 % faster***



**based on run-time comparison using the same machine with the same simulation setup*

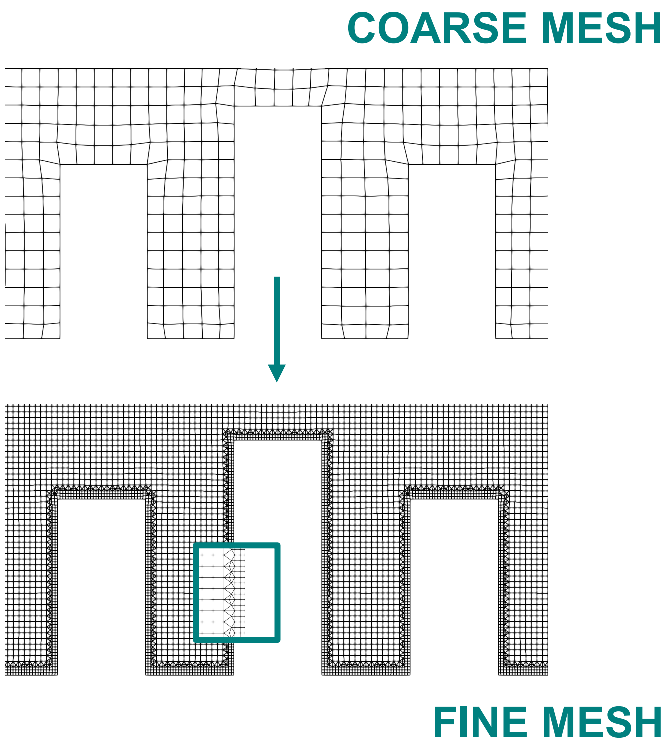
Conclusion and future work

- The current framework proves the feasibility of the approach to aid and enhance CFD simulations with data driven models

- **Future work** will focus on

    - Development similar but more advanced types of interaction between deep learning and CFD

    - New ways of aiding CFD such as leveraging **super-resolution** techniques with CNNs



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