2nd Spanish Fluid Mechanics Conference
Barcelona (2 - 5 July 2023)

Fast urban flow predictions through Convolutional Neural Networks.

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Having real-time and accurate numerical predictions of urban wind flow can be extremely useful for developing tools intended to improve citizens' life quality and health. However, traditional methods such as Computational Fluid Dynamics (CFD) are unsuitable for fast prediction. This work proposes using Convolutional Neural Network (CNN) trained with a newly-created vast dataset to enable fast and accurate flow predictions for any urban geometry. The dataset has been generated through high-fidelity CFD simulations of 30 different European Urban areas and 90 meteorological conditions. The geometries were selected to have a wide variety of urban flow patterns and geometrical features allowing the Neural Network (NN) to learn a representative range of urban flow conditions. Then, a CNN was trained to reproduce the urban wind flow for any urban geometry and meteorological condition. The strategy allows for predicting accurate mean wind flow in urban areas that have not been seen in training time, showing good generalization properties.

1 Introduction

Real-time urban wind flow predictions may help improve citizens' life quality and health since they would allow taking instantaneous countermeasures to mitigate urban pollution, for instance. CFD has been traditionally used to have a detailed insight into urban flow behavior. However, CFD is not suitable for fast prediction due to its complexity and computational cost, even using low-fidelity models such Reynolds-Averaged Navier-Stokes. Thus, alternative methods are needed.

In recent years, advances in machine learning (ML) allowed leveraging the enormous volume of data generated through CFD simulations to develop data-driven reduced models to obtain numerical predictions at a reasonable time, cost, and effort (1). Urban flows have not been an exception.

In particular, generative models have been used to produce CFD-approximated solutions. Mokhtar et al. used cGANS to predict the wind flow on urban area patches (2). However, the authors highlighted the necessity of more extensive datasets and point out the unavailability of public urban flow databases(2).

The present work is intended to create a model capable to generate accurate two-dimensional (2D) CFD-like predictions for any urban geometry without needing to perform preliminary CFD studies on it. To do so, a vast dataset with more than 20×10^3 samples has been generated to train a CNN that takes urban geometrical and meteorological parameters as input and produces the corresponding wind flow map for the specified conditions.

2 Dataset Generation

Good Generalization capabilities are one of the main goals of the proposed model. To achieve this target, a careful selection of urban geometries has been carried out. The purpose is to obtain a rich dataset containing a wide range of flow conditions and geometrical features typical of urban areas.

2.1 Geometry selection criteria

Thirty actual European urban areas of 1 km2 have been selected. Statistical analysis has been carried out to select the geometries, ensuring their representativity of the typical urban configurations that can be found in European cities. Specifically, k-means clustering has been performed from geometrical and land use parameters. The geometries showing less uniform distributions and the less cross-correlated ones (which ensures geometrical variety) have been selected.

2.2 High-fidelity wind flow simulations

Then, high-fidelity simulations were performed on the 30 selected geometries with three different wind directions, resulting in 90 micrometeorological conditions. Wall-Modeled Large Eddy Simulation has been performed to ensure accurate mean flow data. The Vreman model has been used as a subgrid model, while an equilibrium wall function with roughness has been used to deal with the near-wall areas. On the other hand, periodic conditions have been prescribed in the wall-parallel directions while the flow motion has been enforced through a constant pressure gradient. This strategy has been successfully tested to simulate Atmospheric Boundary Layers (3).

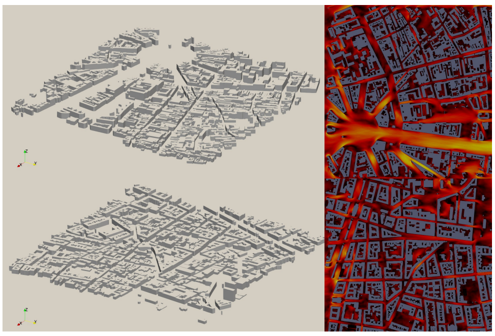

Figure 1: Urban geometry and horizontal-section mean flow dataset samples.

3 Neural Network Architecture

The proposed strategy relies on an image-to-image translation problem. For this purpose, a fully convolutional U-net has been chosen. The NN takes 2D graphical data of the urban geometry at a given height and translates it into a 2D wind flow map.

4 Data Encoding

The target is relating geometrical and meteorological conditions with their corresponding wind flow. For the NN efficiently establish this relation, it is crucial selecting the variables which enclose the most relevant problem information, and encode it into a format that can be used as input for the NN. In the present case, the urban geometrical structure has been represented as a mask distinguishing between fluid/solid areas, and the building height to give the 3D context of the original geometry on which the CFD simulation was performed, and the distance to the solid walls, a flow-relevant quantity. Regarding the meteorological data, the wind direction is assumed to be horizontal. Thus, for different wind directions, the input geometry has to be rotated accordingly. For the wind speed, Re-independence is assumed, and thus, the solution is scaled to match actual conditions.

5 Preliminary results

Preliminary results show that the NN achieves a good generalization degree. In Figure 2, a comparison between the NN-predicted wind field and its corresponding ground truth for a validation dataset sample is shown. However, statistical analysis shows that the model tends to overpredict mid-range wind speed areas and underpredicts extreme wind speed regions (Figure 3).

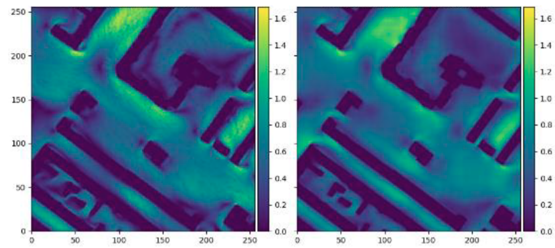

Figure 2: Comparison between the NN wind field output and the corresponding ground truth of a validation dataset sample.

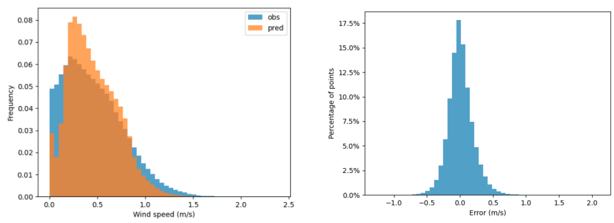

Figure 3: Averaged error frequency distribution as a function of wind speed for all the predicted points in the validation dataset (left) and absolute error frequency across the predicted domain (right)

6 Conclusion

A general predictive wind flow model for urban areas is presented. A vast dataset has been created to obtain good generalization properties for geometries not seen in training time. Reasonable generalization capabilities have been obtained with a large portion of the predicted points in a low error range. However, the NN tends to overpredict mid-range velocities and to underpredict extreme values, especially, low wind speeds. Further improvements will be conducted to enhance the current accuracy.

References

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