August 27-31, 2023
FLORENCE - ITALY
ICWE 16
16th International Conference on Wind Engineering

A multi-fidelity machine learning framework for urban wind energy harvesting over a high-rise building

Anina Šarkić Glumac[1], Onkar Jadhav[2], Stephane P.A. Bordas[3], Bert Blocken[4,5]

[1]*University of Luxembourg, Interdisciplinary Centre for Security, Reliability and Trust (SnT), Legato Team, 6 Avenue de la Fonte, Esch-sur-Alzette, 4364, Luxembourg, anina.glumac@uni.lu*
[2]*University of Luxembourg, Interdisciplinary Centre for Security, Reliability and Trust (SnT), Legato Team, 6 Avenue de la Fonte, Esch-sur-Alzette, 4364, Luxembourg, onkar.jadhav@uni.lu*
[3]*University of Luxembourg, Department of Engineering, Institute of Computational Engineering, Legato Team, 6 Avenue de la Fonte, Esch-sur-Alzette, 4364, Luxembourg, stephane.bordas@uni.lu*
[4]*Anemos BV, Spechtendreef 3, 2460 Lichtaart, Belgium, bert.blocken@anemos-aero.com*
[5]*Building Physics and Sustainable Design, Department of Civil Engineering, Leuven University, Kasteelpark Arenberg 40, Leuven, 3001, Belgium*

SUMMARY:
High-rise buildings have the potential for wind energy harvesting as earlier studies indicated that high wind speed regions can be present above the roofs. Computational fluid dynamics (CFD) represents an attractive tool for estimating the flow fields around high-rise buildings. High-fidelity Large Eddy Simulation (LES) and low-fidelity Reynolds-averaged Navier-Stokes simulations (RANS) are the two possible choices for performing CFD computations. LES has the potential to provide more accurate and reliable results than RANS. However, LES entails a much higher computational costs. In order to take advantage of the main benefits of these two CFD approaches, a multi-fidelity machine learning (ML) framework is investigated to improve the prediction of velocity and turbulent intensity components over the high-rise building for the entire wind rose. The main aim is to ensure the simulation accuracy while maintaining the computational efficiency. The study explores the optimal machine learning setup considering aspects such as: domain size, dominant features, number of training LES simulations, etc. The artificial neural network is shown to perform best among considered machine learning models. The study also demonstrates the importance of data handling and pre-processing techniques.

Keywords: Machine learning, CFD, Urban wind energy harvesting

1. INTRODUCTION

Wind power is one of the extensively used and fastest growing renewable energy sources. In 2021, the global wind power capacity was 743 GW, 14% more than the previous year (Lee and Zhao, 2021). Particularly, the use of wind turbines in urban environments has attracted increasing attention (Stathopoulos et al., 2018). In practice, due to the complexity of the heterogeneous terrain, wind tends to be more turbulent and less predictable in urban areas. This causes inevitable challenges for wind energy potential assessment.

The traditional way to access the wind energy potential relies on the atmospheric boundary layer wind tunnels. However, in recent years, computational fluid dynamics (CFD) has successfully provided a way to determine flow patterns and has contributed to understanding the wind flow above buildings. However, routine use of CFD still requires significant progress to capture the right balance between the accuracy of the results and the efficiency.

This study investigates a multi-fidelity machine learning framework to improve the prediction of velocity and turbulent intensity components over the high-rise building for the entire wind rose. It aims ensuring the simulation accuracy while maintaining the computational efficiency, by relating a large number of low-fidelity RANS simulations to a small number of high-fidelity LES simulations. The main question tackled in this study is 'What data should be used?'. Thus, the study provides several optimisation studies that deals with accessing the dominant features (i.e. input ML variables), accessing the optimal size of the ML training domain and most importantly, determining the number of costly LES simulations needed for the training. This multi-fidelity machine learning framework will be used to access the wind energy harvesting potential over the isolated high-rise building.

2. COMPUTATIONAL FLUID DYNAMICS MODELS

The considered flat roof high-rise building case is related to the wind tunnel tests presented in (Hemida et al., 2020). The model has a square cross-section with edges $B = 133.33\,\mathrm{mm}$, and the height of the building is $H = 400\,\mathrm{mm}$.

All RANS simulations are performed with the same domain and grid. The domain size is $L \times B \times H = 6.8 \times 6.8 \times 1.6\,\mathrm{m}$, where the height corresponds to the height of the wind tunnel. The upstream length is $5.8H$ and downstream length is $10.8H$. The structured grid containing 0.9 million hexahedral cells is used. Different wind directions are obtained by modifying velocity components imposed at the inflow. The inlet boundary conditions are modeled to match the respective incident wind tunnel profiles. The 3D steady RANS equations are solved in combination with the $k-\omega-$SST model. The SIMPLE algorithm is used for pressure-velocity coupling, and the discretization is done using second-order numerical schemes.

The computational domain for LES is a full numerical representation of the wind tunnel, as shown in Fig. 1 a). The domain size is $L \times B \times H = 13.5 \times 1.8 \times 1.6\,\mathrm{m}$, where the height corresponds to the height of the wind tunnel. The final grid of the simulation has around 27 million cells. Dirichlet conditions on the velocity field with $15\,\mathrm{m/s}$ are specified at the inlet, while the outlet is treated as a pressure-outlet with a constant relative pressure equal to zero and a zero-gradient boundary condition for the other flow variables. All LES simulations are performed using PISO velocity-pressure coupling scheme. The validation of the LES simulations is conducted using available experimental data (Hemida et al., 2020) and it is presented in (Kostadinović-Vranešević et al., 2022). All simulations (RANS and LES) are performed using open-source code OpenFOAM (controle-volume based method).

3. MACHINE LEARNING METHOD

The considered machine learning algorithms are support vector regression, random forest, gradient boosting, and the artificial neural network. To improve the model performance, hyperparameter optimization is performed for each machine learning algorithm.

Output values of machine learning model are velocity components (U_x, U_y, U_z) and turbulence intensity components (I_x, I_y, I_z) as well as the global turbulence intensity I_t above the roof of the high-rise building. Thus, respective and available RANS values are taken as independent input variable, i.e. features. This includes: $U_{x,RANS}$, $U_{y,RANS}$, $U_{z,RANS}$ and I_t. Besides other relevant data that might affect the flow field above the high-rise building are also explored, such as: the normalized height-dependent incident velocity magnitude, the normalized height-dependent turbulence kinetic energy, the mean pressure coefficient, non-dimensional pressure gradient, the spatial position of the cells and the incident wind direction.

To optimize the machine learning dataset that considers the flow over the high-rise building, several aspects needs to be considered:

- The size of the considered machine learning domain: Shrinking the size of the domain over the high-rise building might seem counter-intuitive, as in general, machine learning algorithms usually perform better with more data. However, if much of that data is irrelevant, increasing data does not necessarily improve the model performance. Besides, filtering out unnecessary data leads to more computationally efficient model as less training data reduces the computational time.
- The number of features: Similarly as mentioned in the previous point, ambiguous features from the training set ensures less noise during the training phase and improves the quality of the model. Furthermore, less data demands less storage space and eases the difficulty of optimizing a function with too many input variables. Thus, feature engineering can reduce the error drastically and additionally can achieve faster training since the inferior features are eliminated.
- The number of necessary training LES simulations: It can be expected that prediction accuracy of the multi-fidelity framework increases as more results of the LES simulations are used as training data. Yet, LES simulations are very computationally costly. Thus, the machine learning training dataset should consider the optimal, i.e. minimal, number of LES simulations. To facilitate this goal, the full dataset is created that consists of the RANS and LES simulations at 7 different wind directions: 0°, 7.5°, 15°, 22.5°, 30°, 37.5°, 45°. Given the symmetry of the building, these wind directions cover the entire wind rose.

4. RESULTS

The training of the machine learning algorithms is performed on the training dataset with two extreme wind direction results $\{0°, 45°\}$. Those trained machine learning models are then tested for all the intermediate wind directions. Based on R^2 values, it is noticed that the 15° test case gave comparatively weaker predictions than other test cases. Tab. 1 presents the comparison based on R^2 values among the machine learning models after hyperparameter optimization for the 15° test case. One can see that the artificial neural network model outperforms the rest of the models. Moreover, Tab. 1 shows that the artificial neural network model performs satisfactorily for all velocity and turbulent intensity outputs expect U_z (as $R^2 > 0.8$). Velocity profiles plotted in Fig. 1 show that all models give satisfactory results for the U_x and U_y outputs, where as they fail in predicting U_z, as observed in Tab. 1.

Table 1. Test RMSE and R^2 values of the selected models trained on $\{0°, 45°\}$ wind direction datasets and tested for the 15° wind direction.

Models	Support Vector Regression		Random Forest		Gradient Boosting		Neural Network	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
$U_x[m/s]$	0.7364	0.1485	0.8259	0.1191	0.8254	0.1200	0.8300	0.1190
$U_y[m/s]$	0.9484	0.0506	0.9161	0.0661	0.9595	0.0472	0.9213	0.0630
$U_z[m/s]$	0.2488	0.1144	-1.6041	0.4369	-0.3825	0.1679	0.4611	0.0961
$I_t[\%]$	0.7513	0.7461	0.7662	0.7384	0.8486	0.6090	0.8959	0.4825
$I_v[\%]$	0.7750	0.7260	0.7767	0.7117	0.8432	0.6043	0.8499	0.5934
$I_w[\%]$	0.5790	0.7431	0.6171	0.6474	0.7546	0.5573	0.8009	0.5109
$I_u[\%]$	0.8017	0.9164	0.7720	0.9781	0.8654	0.7590	0.8711	0.7460

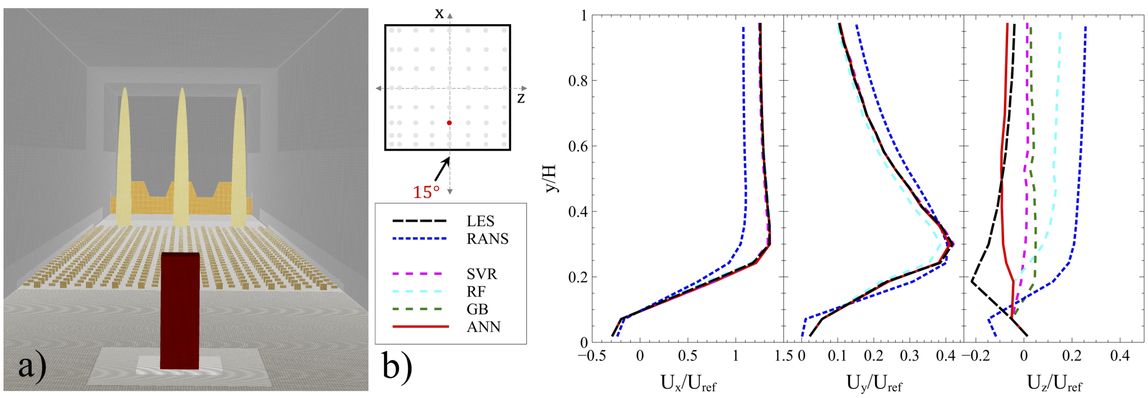

Figure 1. a) LES computational domain with the high-rise building; b) a comparison among LES and different ML models trained on $\{0°, 45°\}$ wind direction datasets and tested for 15° wind direction. The velocity profiles related to the point on the rooftop marked with the red dot.

The study will present the results of all mentioned optimisation procedures. In particular, it will focus on exploring different ML tools to minimize the number of LES needed simulation for the training.

ACKNOWLEDGEMENTS

The author A.Š.G. and co-author O. J. would like to acknowledge the support of the "Soutenu par le Fonds National de la Recherche, Luxembourg" (FNR) for funding the CORE Junior project DATA4WIND - "Data-Driven Approach for Urban Wind Energy Harvesting", C19/SR/13639741.

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