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A data-driven surrogate model framework based on CFD simulations to accelerate wind energy yield assessment

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SUMMARY:
A data-driven surrogate model is developed using deep neural networks, trained from a set of CFD simulations to predict velocities on a 3D grid for a specific inlet velocity condition. The objective is to considerably reduce the number of CFD simulations to be performed when assessing the annual wind energy yield of rooftop micro wind turbines. Steady, incompressible RANS simulations are performed to obtain the wind velocities in the Northern District region of Brussels, Belgium using a modified k-ω SST turbulence model implemented with an improved Atmospheric Boundary Layer approach. Velocity fields from simulations serve as the labels to train the surrogate model, and their corresponding inlet velocity conditions are the features. Prediction of the 3D velocity field is then performed for a new inlet velocity,and the performance of the trained model is assessed by comparing the results with the ones obtained from the CFD simulations. Based on the obtained velocity fields, rooftop locations with high velocities are chosen for the wind turbine installation, and the annual energy yield is calculated at each of these locations. Finally, the speedup in computational time obtained by utilizing a surrogate model in conjunction with CFD for a complete assessment of annual wind energy yield is discussed.

Keywords: CFD, machine learning, wind energy

1. MOTIVATION

Machine learning (ML) is a rapidly growing field that has the potential to revolutionize the way we analyze and simulate Computational Fluid Dynamics (CFD) problems. Wide varieties of ML applications within CFD range from their application to resolve near-wall modeling in wall-bounded turbulent flows, to characterize inflow conditions for turbulence simulations, to define closure models for RANS simulations, as well as for surrogate modeling amongst others (Vinuesa et al., 2022; Brunton et al., 2020). Specifically, Deep Neural Networks (DNNs) have been extensively used to create data-driven surrogate models, where high fidelity results from CFD analysis are used to train a model for different input conditions and instantaneously predict the results for a new condition (Brunton et al., 2020). In the context of CFD simulations for the built environment, surrogate modeling is widely used (Gan et al., 2022; Ding et al., 2019). The main objective of a surrogate model is to quicken CFD simulations while maintaining the same order of accuracy (Calzolari et al., 2021). With an accurately trained model, it is possible to achieve speedups up to 50000 times compared to a conventional RANS simulation (Tanaka et al., 2019). Moreover, using a pre-trained surrogate model does not require any knowledge of the underlying physics, thanks to the training data being from physics based CFD simulations.

One of the primary applications of CFD in the built environment is the assessment of wind energy potential in an urban landscape using micro wind turbines (Juan et al., 2022; Shiraz et al., 2020). An accurate assessment of energy yield, say on building rooftops, requires multiple CFD simulations to be performed per wind direction to obtain a probability distribution of power output (Shiraz et al., 2020). In the present work, a surrogate model based on DNNs is presented, with which the total number of CFD simulations to be performed for the energy yield assessment can be considerably reduced, thereby greatly cutting down the computational time and cost.

2. METHODOLOGY

The Northern District of Brussels, Belgium, a neighborhood that has the ambition to become a Positive Energy District, is proposed as a case study. CFD simulations using the open source FVM-based solver OpenFOAM v7 with an improved Atmospheric Boundary Layer (ABL) framework implemented on a modified k-ω SST RANS model (Bellegoni et al., 2022; Parente et al., 2011) have been developed to assess the wind energy potential. The steady state, incompressible simulations were completed for multiple inlet velocity conditions per wind direction based on wind statistics obtained from the nearest meteorological station.

The machine learning framework was implemented in Python using the Keras library, which is a high-level package built on top of the Tensorflow API. A surrogate model was created using DNNs, which take as input the inlet velocity conditions and predict the wind velocities on a low fidelity 3D grid. Results from CFD simulations were used to train the model, and the wind velocities on the 3D grid served as labels and their corresponding inlet conditions as features. The trained model was then used to obtain the 3D velocity field for a new inlet velocity. The obtained ML-based velocity field was compared with the CFD data to gauge the accuracy of the surrogate model.

Once multiple velocity fields were obtained per direction, the annual energy yield was estimated. The estimation depends on the choice of the wind turbine and its associated parameters such as the cut-in speed, cut-off speed, etc. Optimal rooftop locations showing high wind velocities were chosen as possible candidates for the wind turbine installation. The local wind power was calculated at these locations using the multiple velocity fields obtained from the individual simulations/ML prediction. A two-parameter Weibull curve was fitted to the calculated wind powers using statistical wind data from a meteorological station (see Fig. 1). Finally, the total energy yield for that particular direction was obtained by integrating the Weibull curve. A similar procedure was performed for all the relevant directions and the total annual energy yield was computed through a weighted sum of the individual contributions of each wind direction and their corresponding annual frequencies (obtained from meteorological wind statistics). Moreover, energy yields for different wind turbine designs and rooftop locations were calculated to highlight the differences in yield for each model and implementation.

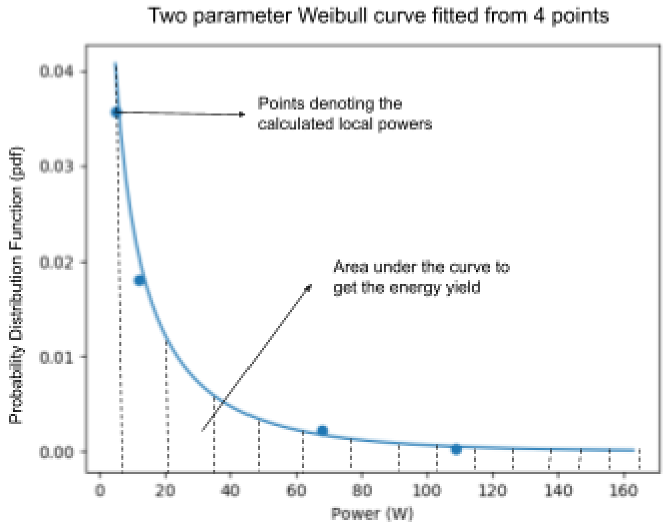

Figure 1. An example of a two-parameter Weibull curve used to calculate wind energy yield for a particular direction, location and wind turbine design.

3. RESULTS

A surrogate model was first tested using a tutorial case from the OpenFOAM training library called *windAroundBuildings*. RANS simulations were performed for inlet velocity conditions of 2, 3 and 10 m/s. The obtained velocity fields were used to train the model. The velocity field was then predicted for an inlet velocity of 7 m/s. A comparison of the results obtained for the CFD and surrogate model are shown in Fig.2 and Fig.3. A very good agreement with CFD is observed.

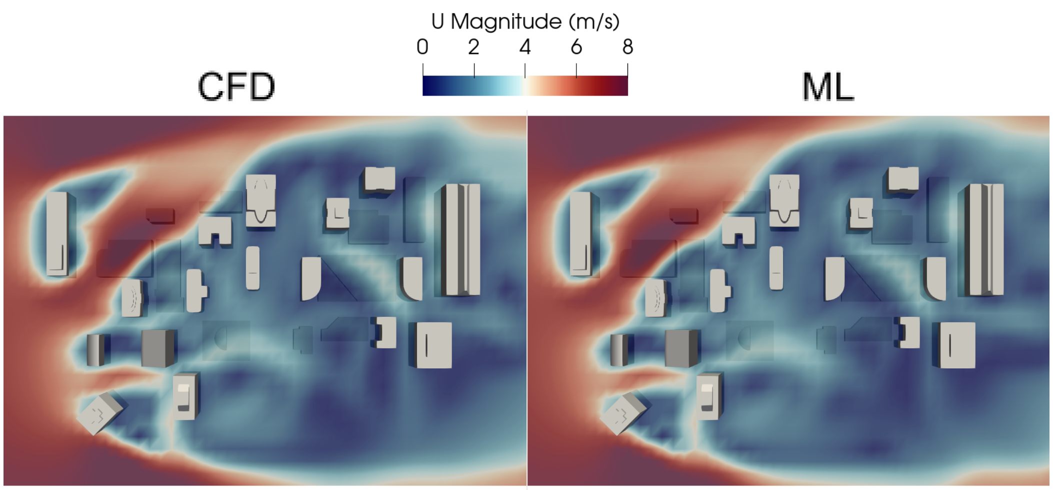

Figure 2. Comparison of velocity contours obtained from CFD and ML at a height of 25m from the ground. Wind is blowing from the left.

A new surrogate model was constructed and trained on the CFD simulation results obtained for a realistic case study based on the Northern district in Brussels. The performance of the model was assessed by a comparison of the predicted velocity field obtained from the surrogate model, and CFD simulation. Following the procedure described in the methodology section, the annual wind energy yield was calculated for multiple micro wind turbine designs and the differences in the yields were discussed. Lastly, the computational time savings obtained by incorporating the surrogate model with CFD for a complete annual wind energy yield evaluation is discussed.

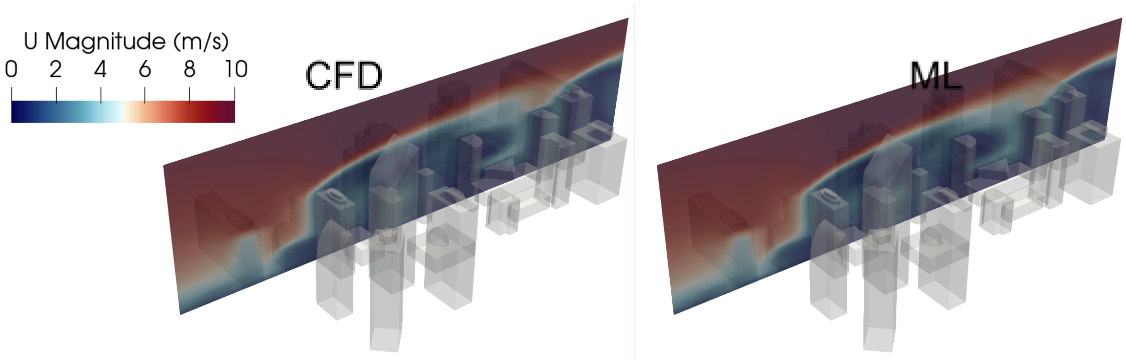

Figure 3. Comparison of velocity contours obtained from CFD and ML on a vertical slice.

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