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

Prediction of mean wind velocity in city block area using machine learning by applying LES results to improve RANS results

Junki Yamaguchi, Takamasa Hasama, Yoshiaki Ito,
Sohei Arisaka, Toshihide Saka

Kajima Corporation, Tokyo, Japan, junki-yama@kajima.com

SUMMARY:
RANS and LES are two types of simulations often used to evaluate wind around buildings. However, although RANS is computationally inexpensive, it has accuracy issues, while LES is more accurate but at greater computation cost. In order to resolve this problem, the authors developed a machine learning model that uses numerical results from RANS as input to output numerical results from LES. It was confirmed that a model with only the building geometry as input could predict mean wind velocity as well as RANS, and the model using RANS results as input in addition to the building geometry further improved the prediction accuracy, reducing the error compared with RANS by about 30%. For the latter model, we also evaluated the accuracy of the model using benchmarks in the CFD field and showed that it reduced the error for RANS.

*Keywords: machine learning, CFD, LES,
RANS, convolutional neural networks*

1. INTRODUCTION

Since wind always occurs around large structures such as high-rise buildings, it is important to investigate the wind environment around the structure in advance using wind tunnel experiments and computational fluid dynamics (CFD) to develop a design plan that does not worsen the wind environment. In the early stages of design, average wind fields obtained by Reynolds-averaged Navier-Stokes Simulations (RANS) are often used to investigate the wind environment for various design alternatives. RANS has a low computational cost, but its predictions are not as accurate as Large-Eddy Simulations (LES), which are more computationally demanding. Therefore, the development of wind environment prediction methods that combine swift calculation with accurate predictions have long been sought.

Recently, there has been concerted research in the field of CFD by utilizing the results of machine learning. For example, a study has been conducted to predict steady-state flow around an object by studying the CFD results with a convolutional neural network,[1)] and a similar method has been applied to wind environment prediction around a building.[2)] In these studies, only the shape of the object, or the shape of the object and the wind direction, were input into the machine learning model.

While it is beneficial to be able to quickly predict the wind environment based on shape alone, it would be very practical if more accurate predictions could be obtained with RANS-like computational complexity, assuming that such results can be used for more accurate studies. In this paper, we propose a method to improve the prediction accuracy of machine learning by adding RANS results as inputs for predicting the wind environment around buildings and report the results of applying this method to the prediction of wind speed fields around city blocks.

2. MODEL AND DATA

In this paper, the machine learning model into which the height, building shape, wind direction, distance from the building of the horizontal plane to be predicted, building height, and information near to the horizontal plane is input, is called Model A. Meanwhile, the one that inputs the results from the RANS wind speed 3-component calculations in addition to the inputs for Model A is called Model B. The supervised data are the results of the calculations of the three components of the average wind speed in LES. U-Net++,[4] a type of convolutional neural network (CNN), was used as the machine learning method.

The data used for machine learning were the results of calculations for the three city blocks shown in Figure 1, for RANS and LES, respectively. The calculations were performed on a 1/400-scale model that reproduced the wind tunnel experiments. The computational mesh with Octree mesh method [5] is the same for both RANS and LES, with approximately 50 million elements. For RANS and LES calculation, Helyx -3.4.0 was used [6]. The standard k-ε model was adopted for RANS and Second order upwind scheme was applied for the convective term, while second order central scheme was applied for the diffusion term. Wall-Adaptive Local Eddy (WALE) model [7] was as the sub-grid scale (SGS) model for LES. WALE model constant C_w = 0.39. Other LES calculation conditions were same with previous literature[8]. The wind direction angle was calculated for 16 directions, rotating from 0 to 360 degrees in 22.5-degree increments. The data representing the RANS and LES results were created by linear interpolation from the city block area indicated by the red box in Figure 1 to an area of the same dimensions with 769 × 769 × 399 cells in the X, Y, and Z directions. Each divided cell has as its component the time-averaged wind speed in the X, Y, and Z directions. The data representing the building shape were 3-dimensional data of 769 × 769 × 399, with the building occupancy in each cell as a component. For training, these data were sliced in the XY-plane and further trimmed to 512 × 512 in the center of the city block to create 2-D data. As for the division of the data for training and testing, the three city blocks calculated for 67.5 degrees out of 16 wind directions were used only as test data, and the others were used only for training.

3. RESULTS AND DISCUSSION

We used Euclidean distance $d(v, \hat{v})$, hit rate, and FAC2[9] as accuracy indices. Let $v = (v_1, v_2, v_3)$ be the wind velocity vectors resulting from the reference LES calculation and $\hat{v} = (\hat{v}_1, \hat{v}_2, \hat{v}_3)$ be the wind velocity vectors to compare, and let the Euclidean distance be

$$d(v, \hat{v}) = \sqrt{(v_1 - \hat{v}_1)^2 + (v_2 - \hat{v}_2)^2 + (v_3 - \hat{v}_3)^2}. \tag{1}$$

The hit rate and FAC2 were calculated by comparing the scalar values of the wind speed vectors for each cell with respect to the data for one wind direction, with the true value v being the result of the LES results.

Table 1 shows the average values of the accuracy indices for each model over the entire test data.

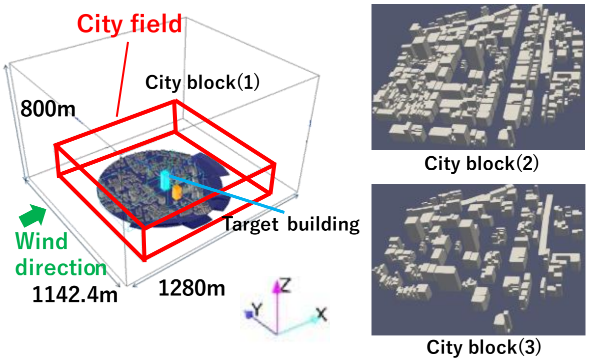

Fig 1. Example of analysis area and city blocks in CFD

Table 1. Average accuracy of test data

	Model A	Model B	RANS
Euclidean distance	0.581	0.386	0.580
Hit rate	0.863	0.918	0.899
FAC2	0.965	0.982	0.972

The smaller the Euclidean distance or the closer the hit rate or FAC2 value is to 1, the better the model can be considered to reproduce the LES calculation results. The average value of the accuracy index for each height is plotted for city block (2) in the test data as shown in Figure 2.

Table 1 shows that Model A is able to predict the LES as close to RANS as possible, and the same tendency as in the case of a single building in the previous report can be seen. However, a comparison of Model A and RANS in Figure 2 shows that Model A has a problem with prediction accuracy in the mid- and low-rise areas compared to RANS. This is due to the fact that Model A is not able to cope with the complexity of the flow field of the city block in the relevant area, and it is considered necessary to increase the types of city blocks to be trained in order to improve the generality of the model. As shown in Table 1, Model B improves on the Euclidean distance of RANS by about 33%. Furthermore, a comparison of Model B and RANS in Figure 2 shows that Model B performs better than RANS across all indices at all heights. However, the accuracy for the low-rise area tends to be lower than that for the high-rise area. This can be attributed to the complex flow field formed by the city blocks, as well as the fact that the RANS results themselves have larger errors in the low-rise portion of the model.

An example of scalar wind speed contours in the case of city block (3) for the test data in each model is shown in Figure 3. Here, the distribution of wind speed ratios is shown, standardized by the inflow wind speed within the XY cross-section at a height of around 6 m. Overall, both Model A and Model B have contour plots similar to LES and RANS.

Figure 4 shows the distribution of Euclidean distances between the LES and the velocity vectors of each model at heights of around 6 m and 40 m. It can be seen that Model B corrects for RANS errors within the red dotted line in the LES-RANS distribution at around 6 m and around the corner of the building. Comparing the contour maps around 40 m in Figure 4, Model B shows improvements in the separation caused by the building and in the backwaters, indicating that machine learning tends to improve the flow field, which RANS is not good at.

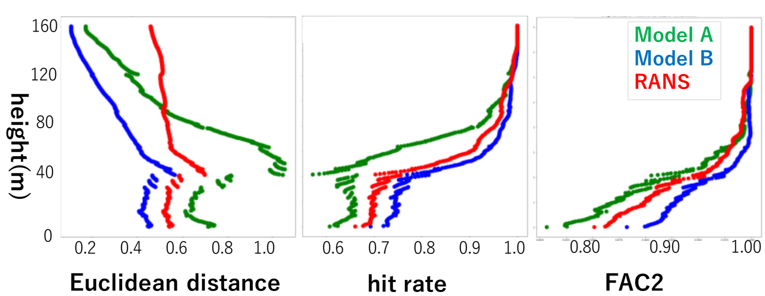

Fig 2. Comparison of average accuracy indices for each height

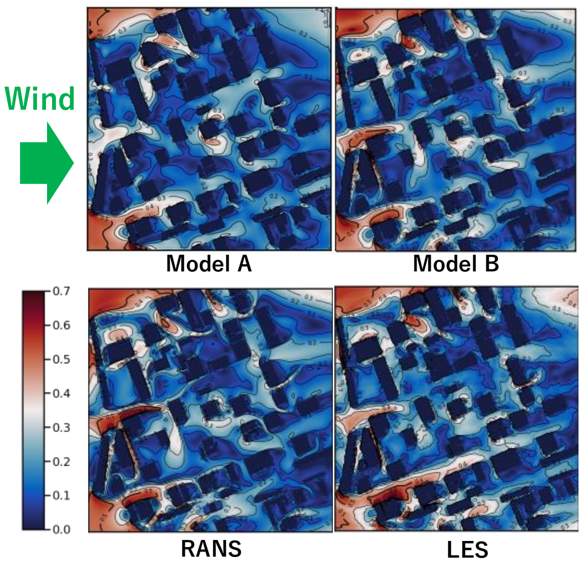

Fig 3. Distribution of scalar wind speed ratio (around 6 m)

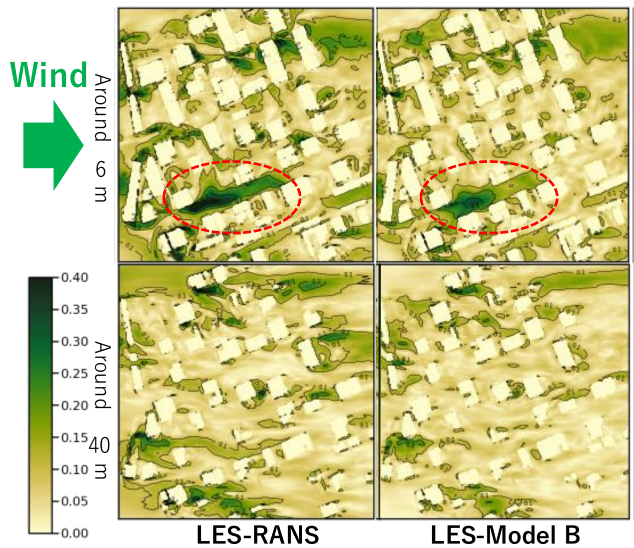

Fig 4. Distribution of Euclidean distance

4. CONCLUSION

In this paper, we develop a new machine learning model that takes into account height direction information, wind direction, and reports the results of accuracy verification. The model achieved, on average, the same accuracy as RANS for inputs of shape, height, wind direction, and other information, indicating that the model can predict qualitative flow fields. The quantitative results showed that the RANS error can be corrected when RANS results are also input. This shows that this technique has the potential to predict the mean wind field close to LES accuracy when using RANS results, even for when complex flow fields can occur, such as in city blocks.

REFERENCES

1) L. Ladický, S. Jeong, B. Solenthaler, M. Pollefeys, and M. Gross, “Data-driven fluid simulations using regression forests,” *ACM Trans. Graph.*, vol. 34, no. 6, pp. 1–9, 2015
2) Y. Kato, "A Study on Building Wind Prediction Method Using Convolutional Neural Network - Wind Speed Distribution Prediction for a Single Building," JIAA Conference (China), pp. 147-148, 2017.
3) Arisaka et al: Prediction of Mean Wind Speed Field around Buildings by Machine Learning with RANS as Input and LES as Output, Annual Meeting of the Japan Society of Fluid Mechanics, 2019.
4) Zhou et al: A Nested U-Net Architecture for Medical Image Segmentation, Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support, 2018.
5) P. J. C. F. Coelho, P. and M. G. Carvalho, “Calculation of laminar recirculating flows using a local non-staggered grid refinement system,” International Journal for Numerical Methods in Fluids, vol. 12, pp. 535–557, 2007
6) https://engys.com/products/helyx
7) D. F. Nicoud, F., “Subgrid-scale stress modelling based on the square of the velocity gradient tensor,” Flow, Turbulence and Combustion, vol. 62, pp. 182–200, 1999.
8) Tetsuro TAMURA, Yoichi KAWAMOTO, Mitsuo YOKOKAWA, Large-Eddy Simulation of Wind Pressure Prediction for High-Rise Building on Urban Block, 14th International Conference on Wind Engineering At: Porto Alegre, Brazil
9) Okaze et al: Large-eddy simulation of flow around an isolated building: A step-by-step analysis of influencing factors on turbulent statistics, Building and Environment, 2021.