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Predicting Pedestrian-Level Percentile Wind Speeds from Second-Order Statistics with Convolutional Neural Networks

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SUMMARY

This study proposes a new approach to efficiently predict percentile wind speeds around buildings using a convolutional neural network (CNN) as a surrogate model of computational fluid dynamics approaches. The training data were obtained from a large-eddy simulation (LES) of flow over a staggered array. The CNN model is designed to predict six percentile wind speeds at the left-bottom point of an input region based on the distributions of mean and standard deviation of the wind speed within the input square region. Sensitivity analysis of the input areas shows that the smallest area achieves the lowest normalized root-mean-square error, indicating that the spatial distribution of basic statistics are critical variables on determining low-occurrence pedestrian winds. Consequently, CNN models accurately reproduce percentile wind speeds, even in regions with sharp spatial variations.

Keywords: *Large-eddy simulation, Convolutional neural network, Urban wind environment, Pedestrian-level wind, Percentile wind speeds.*

1. INTRODUCTION

Promptly estimating pedestrian-level wind conditions, especially very strong and weak winds, is essential for evaluating outdoor safety and comfort in urban environments. Computational fluid dynamics (CFD), particularly large-eddy simulation (LES), is widely used for studying urban wind environments. However, obtaining high-accuracy results typically requires substantial computational time and resources. Artificial intelligence (AI) models can serve as surrogate for CFD, as they can learn complex statistical features of the flow directly from data and provide rapid predictions. Among various AI models, convolutional neural networks (CNNs) can effectively extract spatial features through convolution layers, which might be suitable for predicting strong and weak wind fields greatly affected by building spatial layouts. Leveraging this capability, we have successfully developed CNN models which use the spatial distributions of mean (μ) and standard deviation (σ) of the wind speed for the airflow within the canopy layer of a block array to predict percentile wind speeds (Wan et al. 2025). However, it remains unclear i) how much surrounding spatial information a CNN needs to capture for accurate predictions, and ii) why incorporating such spatial information improves the accuracy of the model. Therefore, this study systematically evaluates the impact of input area size on CNN performance in predicting percentile wind speeds.

2. METHOD

2.1. Data source

In this study, the datasets for training and testing were produced using the parallelized large-eddy simulation model (PALM) (Abd Razak et al., 2013) for airflow over a cubical block array. The blocks are arranged in a staggered configuration with the plan area index of 16% (Figure 1(a)). The building height H is 25 m. Periodic boundary conditions are imposed on the streamwise and spanwise boundaries. The domain height is $4H$. The velocity components, u, v, w, were collected at a pedestrian level of $z/H = 0.1$, and the instantaneous wind speed was determined as $v_a = (u^2 + v^2 + w^2)^{0.5}$. Since the four blocks are geometrically identical, the time series recorded at four equivalent positions were merged, giving a total sampling duration of $T = 1.5\times10^4$ s. The statistics and percentiles were determined during the period T. These results are presented in a $2.5H\times2.5H$ horizontal plan at the $z/H = 0.1$ with a single block, consisting of 159×159 sampling points. Figure 1(b) shows the horizontal distribution of the mean velocity at $z/H = 0.1$. The wind speeds increase along the building sides due to flow separation and a low-wind region develops in the leeward area behind the building. Figure 1(c) shows that the ratio of resolved to total turbulent kinetic energy exceeds 80% across most of the domain, indicating that the mesh resolution and the resulting LES accuracy are sufficient.

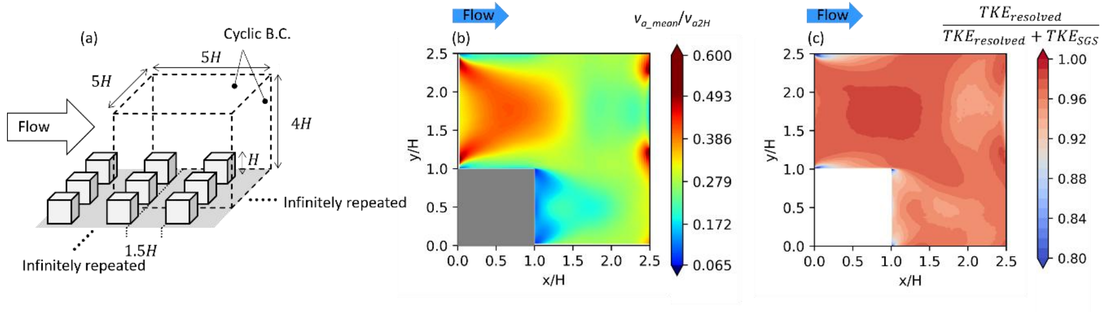

Figure 1: (a) Schematics of numerical domain in LES, (b) horizontal distribution of mean velocity values at $z/H = 0.1$, normalized by wind speed at the height z = $2H$, and (c) horizontal distribution of the ratio of resolved TKE to total TKE at $z/H = 0.1$.

2.2. CNN model

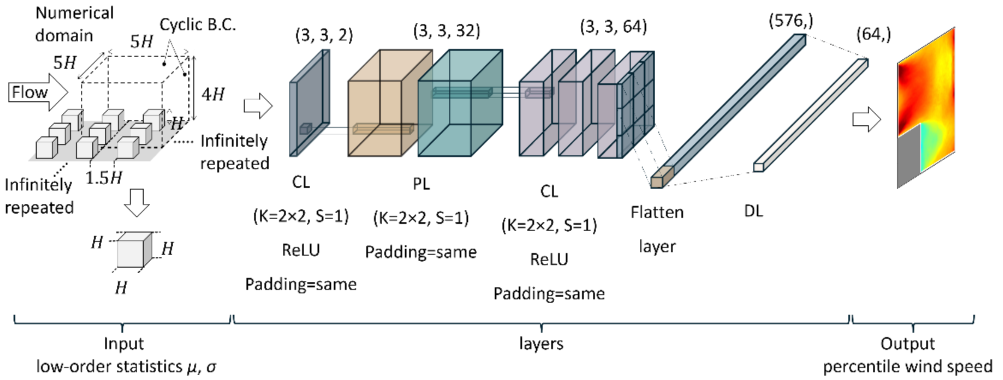

Figure 2: CNN model architecture for predicting percentile wind speeds based on local wind field statistics. Input data are low-order statistics, and six percentiles are estimated as output data.

Figure 2 illustrates the proposed CNN model architecture for predicting percentile wind speeds based on local wind field statistics. Convolutional layers (CL) use 2×2 convolutional kernels (K) with a stride (S) of 1 to extract spatial features and employ the ReLU (Rectified Linear Unit) activation function. The first CL has 32 output channels, while the second, third, and fourth CLs have 64 output channels. Pooling layers (PL) use 2×2 windows with a stride of 1, resulting in 32 output channels. Both convolutional and pooling layers use “padding = same“ to ensure consistent input and output channels for the current layer; the flattened features are passed to a dense layer (DL) that performs feature mapping and dimensionality reduction, with 64 output channels.

The model inputs and outputs were derived from the LES data. The input data was collected at a fixed 3×3 sampling points arranged in a horizontal plan, where the physical size of the square region was varied to examine the effect of the input-area size on prediction. The spacing between points was adjusted accordingly, and regions intersecting the building footprint were removed to ensure data quality. For each region, the input consists of the mean (μ) and standard deviation (σ) at the nine sampling points. The output consists of six percentile wind speeds (99.9%, 99%, 90%, 10%, 1%, 0.1%) at the left-bottom point of the input region, while the top-right points cannot be predicted, resulting in blank areas along those boundaries. Sensitivity tests were conducted for square input areas with side lengths of 0.05H, 0.08H, 0.14H, 0.17H, 0.33H, 0.48H, 0.64H, 0.80H, and 0.95H, with case names defined as CNN2-L, where L denotes the side length of the input area (e.g., CNN2-0.05H).

3. RESULTS&DISCUSSION

The root-mean-square error, RMSE ($\sqrt{\Sigma_i^n(\hat{y}_i - y)^2/N}$) is used for evaluating the model accuracy, where $\hat{y}_i$ is the predicted value at a point i, y_i is the corresponding target value, and n denotes the total number of predictions. Figure 3 presents the normalized RMSE by the mean wind speed at $z = 2H$, v_{a2H}, for the models trained with different input area sizes. Among all cases, CNN2-0.05H exhibits the lowest RMSE since the closely spaced sampling points retain strong local gradients of μ and σ, allowing the CNN to extract informative spatial features. For CNN2-0.08H to CNN2-0.64H, the RMSE values remain similar as the increased spacing weakens local gradients across these cases, resulting in weak sensitivity to the input area. In contrast, CNN2-0.80H and CNN2-0.95H significantly degrade accuracy due to insufficient local variation between points. These results imply that percentile wind speed prediction depends mainly on whether the selected input area can preserve the local statistical gradients of the given statistics.

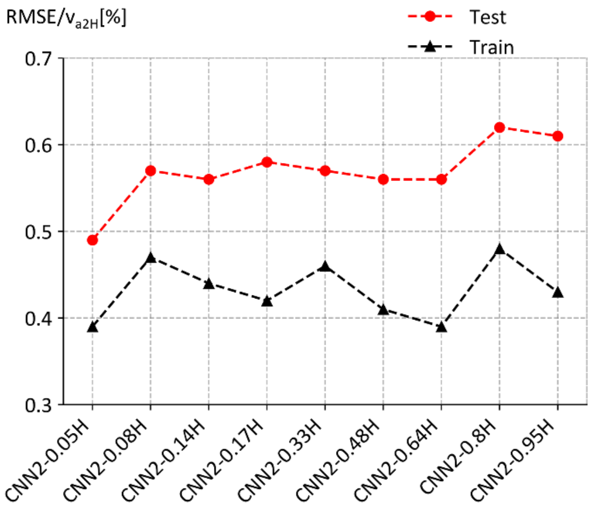

Figure 3: Normalized RMSE values for different input areas.

Figure 4 compares the 99.9 and 1 wind speed percentile distributions at $z/H = 0.1$ between LES and CNN2-0.05H model, as well as their corresponding relative error distribution. CNN2-0.05H accurately reproduces the percentile distribution of the LES results. The relative errors are extremely small at the high percentiles, while the errors at the low percentiles are comparatively larger but still mostly within 10%. This is because the wind speeds are very low at the low percentiles, so even slight fluctuations can lead to a higher relative error.

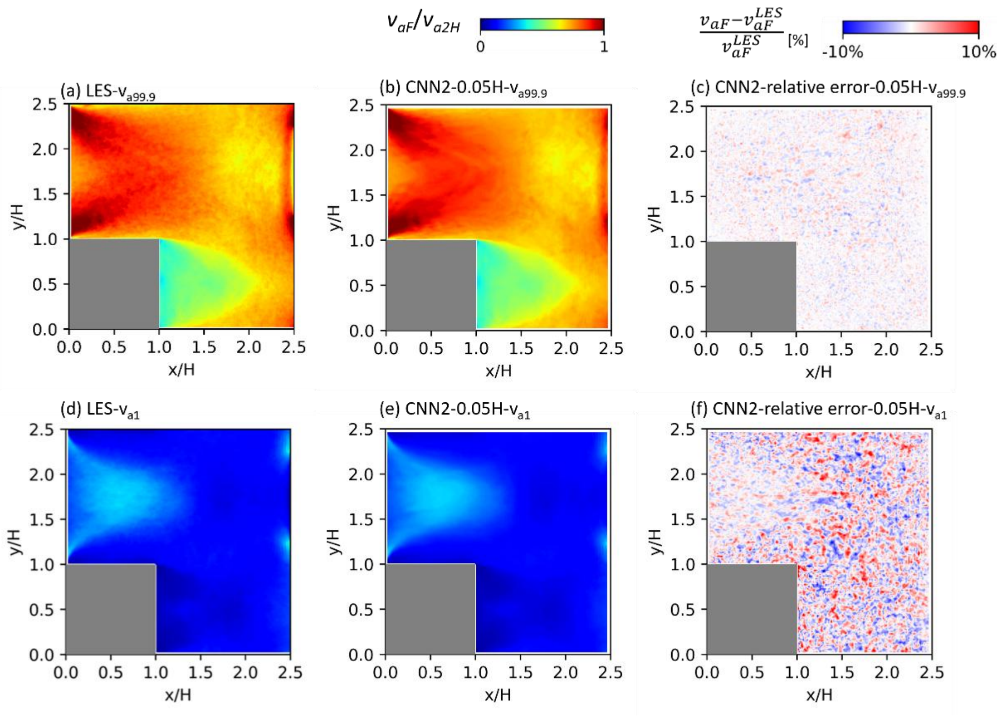

Figure 4: LES and CNN2-0.05H wind speed percentile at $z/H = 0.1$, with the corresponding relative error distributions.

4. CONCLUSIONS

This study demonstrates that the spatial distributions of second-order statistics enable accurate reconstruction of percentile wind-speed fields. The smallest input size (0.05*H*) retains the strongest local gradients and yields the highest accuracy, while moderate sizes (0.08H~0.64*H*) maintain comparable performance until excessive enlargement (>0.80*H*) causes wind gradient information loss and accuracy degradation.

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