Bridging the Gap: Embedding 3D Details into Fast Deep-Learning Model for Pedestrian-Level Wind Prediction

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1 BACKGROUND

In urban areas, pedestrian comfort and safety are paramount considerations in architectural design. Traditionally, studies on pedestrian wind comfort rely on scale model testing or computational fluid dynamics (CFD), which are time-consuming and costly, hindering rapid iteration in early-stage design. This paper presents a deep learning approach for predicting pedestrian-level wind around buildings, focusing on skywalks and lift-up designs. Current research uses 2D projections of geometries, encoding height information to forecast time-averaged velocities at pedestrian height. Our approach embeds 3D details of the skywalks and lift-up designs into the projections, enabling the model to learn flow patterns around these structures and deliver predictions much faster than CFD solutions - We validate our deep learning model's performance on previously unseen configurations, demonstrating its effectiveness in accurately predicting pedestrian-level wind. This approach offers a valuable tool for architects, urban planners, and wind engineers design safer and more comfortable spaces in urban areas.

Lift-up designs provide sheltered outdoor areas beneath elevated buildings, allowing wind to penetrate and ventilate the surrounding areas, improving air circulation and thermal comfort while dispersing pollutants [1–3]. Skywalks enhance pedestrian safety, mobility and provide convenient links between buildings [4]. However, the flow patterns around such structures are often complex with the potential to create difficult conditions for pedestrians.

Recent machine learning approaches to pedestrian-level wind assessments have shown very promising results, with architectures including Convolutional Neural Networks, Generative Adversarial Networks, and Gaussian Process models [5–12]. Despite these advances, current methods use 2D projections of urban morphology, limiting their ability to predict flows around architectural features like bridges or lift-up designs. Weerasuriya, et al trained a neural network to predict flow velocities at discrete locations around isolated lift-up buildings [13] and optimise designs for pedestrian wind and thermal comfort, achieving inference times of less than one minute [14]. Our model can predict the three components of wind across an entire area in fractions of a second, capturing the flow characteristics and interactions between two buildings connected by a skywalk.

2 METHODOLOGY

We developed an automated pipeline to generate 490 unique, simplified geometries, each consisting of two buildings connected by a skywalk, using parametric design ***Figure 1***. The design space for the building geometries includes various dimensions for Building 1, the skywalk, and Building 2. The height (h) for Building 1 and Building 2 ranges from 10 to 100 metres, while the width (w) and depth (d) range from 10 to 80 metres. The distance from the ground (z) is either 0 or 3 metres, and the distance from the datum (y) is set at 0, 10, or 20 metres. The skywalk has fixed dimensions: a height of 3 metres, a width of 20 metres, and a depth of 3 metres. Its distance from the ground (z) is fixed at 6 metres, with the same distance from the datum (y) options as the buildings (0, 10, or 20 metres). We used a Latin hypercube sampling method to select combinations of geometries from the design space. Eight RANS CFD simulations with different wind directions were produced for each geometry using OpenFOAM's steady-state SIMPLE solver with a standard k-ε turbulence model employing the coefficients provided by Hargreaves and Wright [15]. The domain was cylindrical, with a diameter of 1600 m and height of 300 m. The inflow profile was logarithmic with a reference velocity of 5 m/s at 10 m height.

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The CFD data was post-processed into pairs of 256x256 pixel images. The geometry data consisted of two channels containing the heights of the top and bottom of structures. The flow data comprised three channels storing the velocity components 2 m from the ground. The area of one pixel is 0.75 m². The generated data was split into training, validation, and test sets with a ratio of 7:2:1.

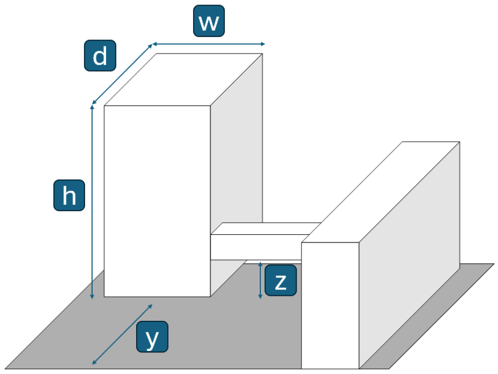

Figure 1, Schematic representation of the geometries.

The model used was an MLP-Mixer modified for this task introduced in [16]. It takes in the two-channel geometry data and returns a three-channel image representing the predicted flow field. A mean squared error (MSE) loss over all pixels was used as the objective function to train the model for 20 epochs, taking approximately 3 hours on a single A100 GPU and achieving a training loss of 0.000052.

3 RESULTS AND DISCUSSION

A test set containing 392 previously unseen geometries was retained to evaluate our deep learning model's performance. The mean inference time for a single image was 0.03 seconds, significantly faster than the CFD solution, which took approximately 4 hours giving the model great potential for uses in optimisation frameworks by facilitating rapid iteration. We used MSE, peak signal-to-noise ratio (PSNR), and structural similarity index (SSIM) to compare the deep learning predictions to the CFD predictions, following the framework introduced in [17]. These metrics provide a good indication of pixel-wise error, image quality, and perceptual error, the ability for humans to make accurate judgment. — These metrics are important in the preliminary design process where results are used to guide direction rather than quantification.

We conducted a series of experiments to determine the optimal set of hyperparameters for this model. We found that reducing patch size and neighbourhood benefits the model. However, the absence of neighbourhood mixing negatively impacts the model's performance, as it removes the ability to consider spatially local information. Conversely, a larger patch size and neighbourhood may introduce unnecessary complexity and noise overwhelming the model. While increasing the model's depth initially aids learning, excessive depth reduces effectiveness, indicating high variance and overfitting. Additionally, increasing the training data size from 30% to 100% of the combined training and validation sets significantly improves model performance. Although the rate of improvement slows between 70% and 100%, the results suggest that further performance gains might be possible with additional training samples.

The best model achieved an average SSIM of 0.991 and PSNR of 42.352 dB, indicating a high degree of similarity and quality when comparing the predictions and the ground truths. Our model captures complex wind flow behaviours around buildings, including downwash on the leading edges, updrafts on the leeward side of lift-up buildings, increased velocity as the wind wraps corners, and reversal of flow direction in the wake regions. ***Figure 2*** illustrates these captured flow features. Additionally, we are able to see that the model correctly predicts decreases in velocity in the vicinity of the skywalk.
To further assess the model's ability to generalise beyond the scope of the training data, we produced additional unseen test samples. These samples included an additional building upwind, designed as either a standard or lift-up structure, to interrupt the approaching flow. The model outputs demonstrated its ability to characterise the resulting flow around the buildings. However, a more in-depth study is

required to fully understand the extent of this capability, encompassing a variety of building densities, configurations, and morphologies.

One limitation of this study is the use of floating buildings in the CFD simulations for the lift-up design geometries. This simplification omitted the core of the building that would realistically support it. However, the results presented here demonstrate that 2D model inputs can be effectively enhanced by embedding a limited set of 3D information, providing the model with enough context to permit accurate predictions for structural design features such as lift-up structures and skywalks.

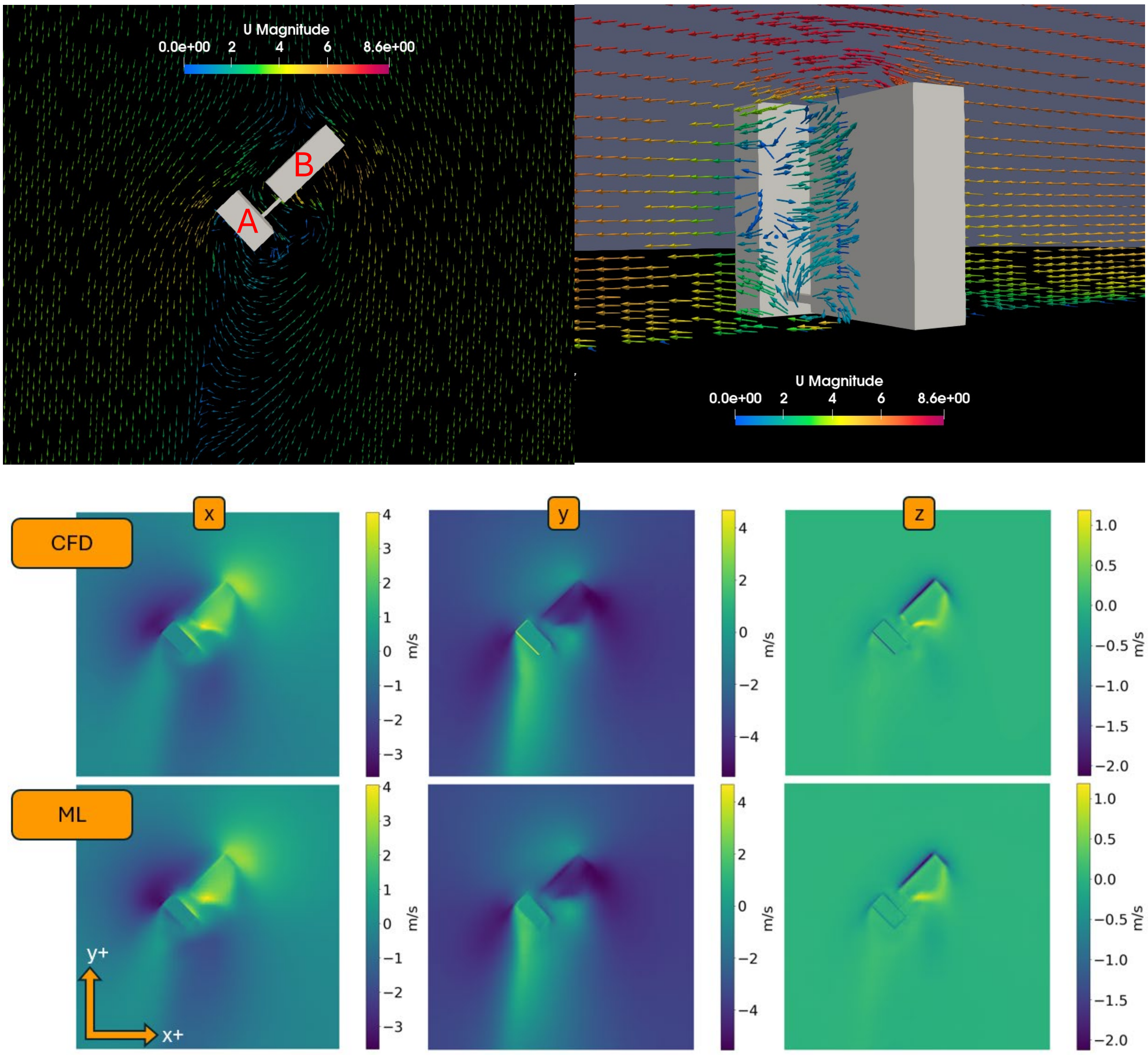

Figure 2, Top: Visualisation of the velocity magnitude computed by the CFD solver for the z-normal plane (left) and x-normal plane (right) for a single geometry with non-lift-up (A) and lift-up (B) buildings. Bottom: Comparison of model predictions and ground-truth for the x-, y-, and z-components of wind velocity for the same geometry.

4 CONCLUSION

This paper demonstrates the capability of a modified MLP-Mixer architecture in predicting pedestrian-level wind flows around lift-up designs and skywalks. The model effectively captures complex flow characteristics and correlates well with CFD solutions across MSE, PSNR, and SSIM metrics. Its high accuracy and rapid inference speed make it a valuable tool for preliminary designs. Further research is needed to explore the model's ability to generalise more complex morphologies. The framework presented here sets a precedent for using surrogate models for structures with intricate design elements such as cantilevers, podiums, and tunnels.

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