

ABSTRACT

Wind tunnel testing remains the primary method for assessing wind effects on civil structures, providing accurate and reliable data. However, such experiments often lack detailed aerodynamic information (e.g., wind velocity and pressure fields) around the structure, leading designers to rely on empirical knowledge rather than physics based rationale. Numerical simulations using computational fluid dynamics (CFD) can address this limitation, but their high computational cost makes them impractical for rapid design assessments in the pre-design phase. Artificial neural networks (ANNs) have recently emerged as a promising technique to overcome the constraints of both experimental and numerical approaches. While ANNs are faster and more cost-effective, their performance is limited by the scarcity of high-fidelity training data. Generating extensive datasets through wind tunnel tests or CFD simulations remains a formidable challenge.

To address these limitations, this study integrates experimental, numerical, and data-driven methods. First, an exploratory study assessed the feasibility of three CFD approaches commonly used in the literature for generating flow fields around an isolated building in an atmospheric boundary layer (ABL) approach flow: Reynolds-averaged Navier–Stokes (RANS) with the RNG $k-\epsilon$ model, detached eddy simulation (DES) based on the Spalart–Allmaras model, and large eddy simulation (LES) with the Smagorinsky subgrid-scale model. The three-dimensional (3D) numerical setup was validated against benchmark wind tunnel data published by the Architectural Institute of Japan (AIJ). RANS is computationally efficient and has been widely used to generate training data for surrogate models, but it failed to accurately capture wake flow characteristics. DES and LES were previously considered too costly for generating deep learning datasets. With recent advances in high-performance computing (HPC), however, they have become feasible at the Reynolds numbers relevant to wind environment assessment around buildings. Both LES and DES yielded improved accuracy over RANS, and LES performed slightly better than DES. Given that DES provided only marginal computational savings, and that LES has been more thoroughly validated for flows around buildings, LES was adopted for dataset generation.

Next, using the validated LES numerical setup, an automated workflow was developed to conduct parametric simulations and generate high fidelity flow field datasets. A comprehensive set of simulations were conducted by systematically varying terrain and building dimensions. All simulations were executed on the HPC resources at Florida State University’s Research Computing

Center. Using this dataset, a U-Net model was trained to predict flow fields on horizontal planes around the building at various elevations relative to the building height. The model was tested on buildings of unseen dimensions exposed to different upstream roughness conditions. The trained network serves as a surrogate for LES, performing inference orders of magnitude faster than the full simulations and enabling rapid assessment of wind effects.

Finally, a standard U-Net learns a purely data-driven mapping from input to output without accounting for flow physics. When trained with a conventional mean squared error (MSE) loss, it tends to predict an averaged flow pattern. This smooths out sharp gradients in separation regions, shear layers, and wakes, and the predicted fields do not satisfy mass conservation. To address these issues, two physics-informed loss functions were devised: one that penalizes gradient errors and another that penalizes violations of mass conservation.

The proposed approach alleviates the computational burden typically associated with CFD, provides reliable predictions of wind flow and pressure fields, and enhances the evaluation of civil infrastructure under extreme wind events. In addition, this framework provides a methodology for developing robust tools for the pre-design and performance assessment of civil structures.