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, this study devises a way to utilize the unique capability of the boundary layer wind tunnel (BLWT) facility at the University of Florida, which can replicate terrains using its mechanized roughness element grid, to capture mean wind speed profiles in the atmospheric boundary layer (ABL). Empirical and semi-empirical wind profile models can capture profiles over terrain with homogeneous roughness, but they do not account for the irregular profiles generated by the erratic roughness configurations observed at some real-world sites. Consequently, three ANN architectures were devised to integrate the most critical terrain features that influence wind profile prediction. Several input parameters were explored to capture proximate and distal roughness changes upstream of the measurement location. The ANNs demonstrated higher accuracy, as their data-driven nature makes them more comprehensive than empirical or semi-empirical models, with the capacity to capture complex nonlinear patterns. Although data-driven models are not as cost-effective or accessible, the insights from this study enhance our understanding of boundary layer physics by identifying key parameters that help capture the wind profile more accurately.

Second, the study moved from modeling the approaching wind flow to modeling its interaction with buildings to capture the wind flow fields around buildings of different dimensions. To this end, 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 ABL approach flow. These were Reynolds-averaged Navier–Stokes (RANS) with the RNG k–ε 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. Because the two required comparable computational time and 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 was 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 introduced. The first penalizes errors in the spatial gradients of the predicted fields, and the second penalizes violations of mass conservation. Once trained, the surrogate model can substantially reduce the computational cost associated with CFD, provide reasonably accurate estimates of the mean and standard deviation of the wind velocity components around buildings, and support feasibility studies of civil infrastructure during the pre-design phase.

Overall, the proposed ANNs offer clear advantages over conventional approaches, providing improved accuracy in predicting mean wind speed profiles and greatly reduced computational cost in estimating flow fields around buildings. In addition, the data generation methodologies developed in

these studies, combining wind tunnel testing with validated LES, provide a framework for building further data-driven models and other artificial intelligence tools to support informed design decisions and the performance assessment of civil structures.