

Wind-borne debris damage estimation for clusters of buildings based on machine learning and CFD simulations

Sejin Kim¹, Fei Ding², Seymour M.J. Spence³

¹Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, MI, 48109, USA, <u>sejinki@umich.edu</u>

²NHERI SimCenter, University of California, Berkeley, CA. 94804, USA, <u>feiding@berkeley.edu</u>
³Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, MI, 48109, USA, <u>smjs@umich.edu</u>

SUMMARY:

Hurricanes are one of the costliest and most devastating natural hazards causing astronomical losses every year in the United States alone. During the last decade, various research efforts have been made to propose engineering-based frameworks to predict damage to, or resilience of, communities subject to hurricanes and help policymakers to make informed decisions in mitigating hurricane-induced risks. This study aims at advancing a recently introduced damage estimation framework for hurricanes that considers explicit modeling of wind-borne debris impact. Two areas of improvement were investigated. First, approaches were introduced for improving the accuracy of building modeling by incorporating detailed information on the building geometry and damage-susceptible components through machine learning-based image segmentation techniques. This overcomes one of the main limitations of many existing methods which use a limited number of archetype buildings to model communities. Secondly, high-fidelity computational fluid dynamics simulations are integrated into the framework for explicit modeling of the interference effects between buildings and therefore a realistic estimation of the peak pressure coefficients.

Keywords: Computational fluid dynamics, Hurricane hazard, Wind-borne debris damage, Vulnerability modeling

1. INTRODUCTION

Over the last decade, there have been many research efforts aimed at estimating hurricane-imposed risks for communities by developing vulnerability models which are able to estimate posthurricane damages and losses (e.g., Abdelhady et al. 2020; Lin et al. 2019). In particular, various computational frameworks have been proposed for the evaluation of building- or component-level damages over entire regions, therefore, aiding policymakers in making decisions that enhance the resilience of their communities against hurricanes. However, these frameworks have several limitations. First, the building archetypes that the frameworks include are very limited. For example, Abdelhady et al. (2020) suggested a wind-borne debris simulation framework that considers a simple gable-roof one-story wooden building as the only archetype for modeling a residential community. This simplification can lead to errors in risk or resilience estimates due to the inevitable differences between the geometric features of each building, such as the number of stories and the roof shape, as well as the location of damage-susceptible components, e.g., windows and doors. In addition, few frameworks account for aerodynamic interference effects from surrounding buildings that can significantly affect peak wind pressures on building surfaces. To overcome these limitations, this study presents an improved framework for debris damage estimation for hurricanes by integrating precise 3D building modeling, through machine learning (ML)-based image segmentation techniques, and computational fluid dynamics (CFD) simulations. Using building polygons obtained from Google Earth while leveraging Natural Hazards Engineering Research Infrastructure (NHERI) SimCenter ML algorithms, region-specific clusters of 3D building models were constructed that are not constrained to any archetype. These building models were subsequently used to construct CFD meshes for region-specific large eddy simulations (LES) to obtain peak wind pressures. Using the results of the CFD simulation, Monte Carlo simulation (MCS) based debris damage estimation was conducted to estimate damage ratios and fragility curves for the building cluster. A comparative study with the method proposed by Abdelhady et al. (2020) was also conducted to validate the effectiveness of the improved framework of this study.

2. BUILDING MODELING

A small cluster of buildings was selected for the case study. Fig. 1(a) reports the selected area which is located in the north part of Atlantic City, NJ. The cluster is composed of eight one-story wooden buildings. Each building has unique geometric features such as roof shape and the number and location of damage-susceptible components, e.g., windows. In order to reflect each of those characteristics during CFD and debris simulation, polygon information was obtained for each building from Google Earth. Fig. 1(b) shows the constructed 3D building models that successfully captured the major geometric characteristics, such as roof slopes/shapes, dimensions, and patios. Non-building objects like trees and cars were neglected during the modeling process.



Figure 1. (a) An 3D image and (b) 3D building models of the investigated area

In addition, to identifying damage-susceptible components, an image segmentation technique was applied based on ML schemes that automatically located the windows and doors for the eight buildings. In particular, BRAILS (Building Recognition using AI at Large-Scale), developed by the NHERI-SimCenter, was applied for this task (Cetiner et al., 2022). Google Street View images, obtained automatically based on the locations of each building via a Google Cloud API, were used as input to BRAILS. In this approach, each pixel of each image was classified into five categories: window, facade, roof, door, and background.

3. NUMERICAL SIMULATIONS

3.1. CFD simulation

CFD simulations were carried out using LES for the eight buildings shown in Fig. 1(b) using

OpenFOAM. Thirty-six wind directions at 10 degree intervals were executed simultaneously by utilizing the computational resources of the Texas Advanced Computing Center of NHERI. The mesh model was generated using the snappyhexmesh method, where the length scale was 1/10, and the number of cells was 2.7 million (See Fig. 2(a)). An exponential wind profile was simulated for which the wind speed at the roof height was 11 m/s and the exponent was 1/4. The Reynolds number was about 5×10^5 . At the termination of a simulation, the pressure distributions on the building surfaces were extracted. The average pressure over each roof panel of the buildings is shown in Fig. 2(b). The size of all roof panels was assumed to be 4 ft x 8 ft. Peak pressure coefficients were estimated for each roof panel, window, and door for all wind directions for subsequent use in the damage estimation model.

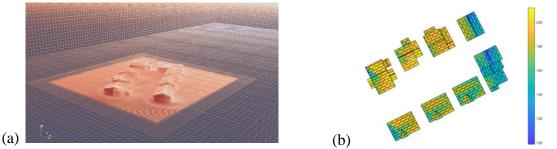


Figure 2. (a) The CFD mesh; (b) mean pressure distribution on the roof panels.

3.2. Wind-borne debris simulation

The estimation of debris damage was conducted by applying the recently introduced vulnerability model presented in Abdelhady et al. (2019, 2020; 2022a; 2022b). In order to simulate debris generated from the upwind communities, the surrounding buildings were also modeled using the gable-roof building archetype introduced by Abdelhady et al. (2020). Time-averaged wind speed and direction time histories for each building location were generated from hurricane trajectories simulated from established parametric hurricane models. The internal and external pressures of buildings were updated for every time step based on the peak pressure coefficients. The pressure coefficients derived from the CFD simulations were utilized for the building components in the target area (see Fig. 1) whereas those of the surrounding buildings were obtained from the Tokyo Polytechnic University pressure database (Tokyo Polytechnic University, 2007). The damage state of each building component (roof sheathing, cover, window, door, etc.) was evaluated, from which the trajectories and impacts of newly generated wind-borne debris were evaluated.

4. PRELIMINARY SIMULATION RESULT

Fig. 3 shows an example of the simulation results for a specific hurricane and the solution representing current approaches, i.e., all building models in the target cluster (the red box in Fig. 3) were modeled with the gable-roof building archetype using the pressure data from the Tokyo Polytechnic University. Each grid indicates the heat map for debris landing and the color of each building shows the damage ratio r_D which is the ratio between the number of damaged components N_D and the number of entire building components N_C . Yellow corresponds to a damage ratio of 10% or more, orange to 20% or more, and red to 30% or more. MCS was conducted to estimate the fragility curves of the eight buildings. In the second stage of the work, the archetypes will be replaced by the building-specific geometries and damage-susceptible

components identified through the ML schemes with peak pressure coefficients estimated from the LES-based CFD simulations. The importance of considering detailed building geometries, specific locations of the damage-susceptible components, and interference effects will be discussed through a comparative study between current approaches and the farmwork of this work.

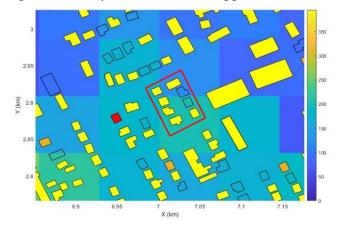


Figure 3. Heat map for debris landing and the damage ratio of buildings (the red box indicates the target area).

5. CONCLUSIONS

This study was focused on the development of a vulnerability model based on the integration of explicit debris modeling, high-fidelity CFD simulation, and ML-based image segmentation techniques for the automatic identification of building geometry as well as damage-susceptible building components. The method was applied to a cluster of buildings in Atlantic City, NJ, with damage ratios and fragility curves estimated through MCS. Through a comparative study, the advantages of the proposed farmwork over current methods are investigated with a focus on providing insights for improving the estimation of community resilience against hurricanes.

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