August 27-31, 2023
FLORENCE - ITALY
16th International Conference on Wind Engineering
ICWE 16

Equivalent turbulence profiles from randomized terrain in a boundary layer wind tunnel and its effects on pressure coefficients

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SUMMARY
The boundary layer wind tunnel facilities, commonly used for assessing wind loads on structures, routinely match 1st and 2nd order statistical wind field models. However, evidence suggests that winds in the roughness sublayer and the inertial sublayer exhibit non-Gaussian higher-order properties. These non-Gaussian properties can influence peak wind pressures, which govern certain structural limit states and play an important role in design. In this project, machine learning methods are employed to identify relationships between roughness element configurations and higher-order statistical properties of the wind field. A semi-automated framework with an active learning portion and a wind tunnel experimental procedure is developed. The learning framework adaptively selects roughness profiles and launches new experiments that learn which profiles create second-order equivalent flow based on the premise that second-order equivalent wind fields can possess different higher-order properties that potentially can be linked to the roughness features of the facility. The differences in the higher-order properties can potentially exacerbate peak pressures and, consequently, the response of structures. The effect of these higher-order characteristics on structures is also studied by investigating the peak pressures on two bluff bodies under different combinations of 2nd order and higher-order equivalent and non-equivalent properties.

Keywords: boundary layer wind tunnel, non-Gaussian, equivalent wind fields, peak wind loads

1. BACKGROUND AND MOTIVATION

This ongoing research project (CMMI 1930389 & 1930625) investigates whether commonly achieved matching of 1st and 2nd order (mean and turbulence intensity) wind field profiles in a boundary layer wind tunnel (BLWT) flow is sufficient for producing consistent peak wind pressures. The hypothesis is that multiple roughness element configurations can produce equivalent second-order wind fields but different non-Gaussian higher-order properties (e.g., skewness and kurtosis) that may produce non-equivalent peak loads.

This study harnesses the recent availability of two tools that, when used in tandem, improve the efficient high-volume throughput of experimental wind tunnel investigations. The control system for an automated, high degree of freedom, rapidly reconfigurable roughness element grid (‘Terraformer’ - Figure 1) and automated instrument gantry are integrated with an active machine learning (ML) algorithm that chooses the next roughness element configuration to investigate based upon an objective and the accumulated outcomes of every previous experiment. A Gaussian process regression based adaptive learning framework searches a bounded but flexible parameter space describing the possible roughness configurations to identify the subspace that corresponds to 2nd order equivalent boundary layer profiles. Then, we investigate the higher order characteristics of the parameter space to select the Terraformer configurations to test two bluff bodies. The next phase will then investigate the effect of the higher order characteristics in the peak pressures on bluff bodies.

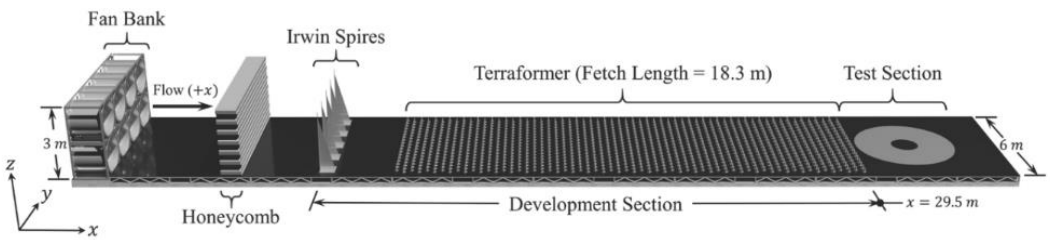


Figure 1. The University of Florida BLWT configuration

2. IDENTIFIYING 2ND EQUIVALENT PROFILES

The following systematic study was used to identify Terraformer configurations that produce 2nd equivalent turbulence profiles in the University of Florida BLWT facility.

2.1. Benchmark profile

A homogeneous baseline terrain was first established as 80 mm height for each of 1116 roughness elements. An automated gantry system was used to move three cobra probes to predetermined locations within a measurement plane to quantify the wind field and establish a benchmark 2nd order profile. This was repeated 25 times to quantify acceptable error bounds among the 25 identically run experiments, i.e. define ‘statistically equivalent’ 2nd order profiles.

2.2. Training set

The Terraformer element grid height scheme was then assigned to describe as a single harmonic in the along wind direction rather than homogeneous, parameterized using wavenumber and amplitude as variables to be identified by the ML algorithm. The parameter space was divided into a 5x5 grid, and an experiment was conducted (wind field quantified) for each of these 25 Terraformer configurations. The 2nd order profile from each of these was compared to the benchmark profile and determined to be either equivalent or non-equivalent. The outcomes were used to train the active ML algorithm for section 2.3.

2.3. Active machine learning

The training experiments informed the initial conditions of an active ML algorithm that was tasked with finding the regions of the Terraformer parameter space that produce turbulence intensity (I_u) profiles that are 2nd order statistically equivalent to the benchmark profile. This combination of automated instrumentation, parameterized Terraformer, and active ML algorithm was then operated without human input, where the next experiment (next Terraformer roughness element configuration) was determined by the ML algorithm. The goal was to identify the region, within the two-parameter space, of equivalent 2^{nd} order behavior, and then probe this region for higher order differences (section 2.4). After enough configurations are conducted, the equivalent second-order parameter space emerges. Figure 2 illustrates the two-parameter space, where the equivalent 2^{nd} order region is the green area, and the non-equivalent second 2^{nd} order region is the yellow area. In the figure, the blue stars indicate the section 2.2 Training Set, and the red dots the section 2.3 Active Machine Learning experiments.

2.4. Higher-order investigation

Section 2.3 identified a continuum of Terraformer configurations that produce I_u profiles that are statistically indistinguishable with respect to 2^{nd} order characteristics (e.g., Figure 2). Referring to Fig 2, much of the non-second-order equivalent space (yellow) was also non-equivalent in higher order properties. Some cases in the second equivalent space (green) were also high-order equivalent. Importantly, several cases that were second-order equivalent were non-equivalent for their higher order properties. This provides the motivation for the next section.

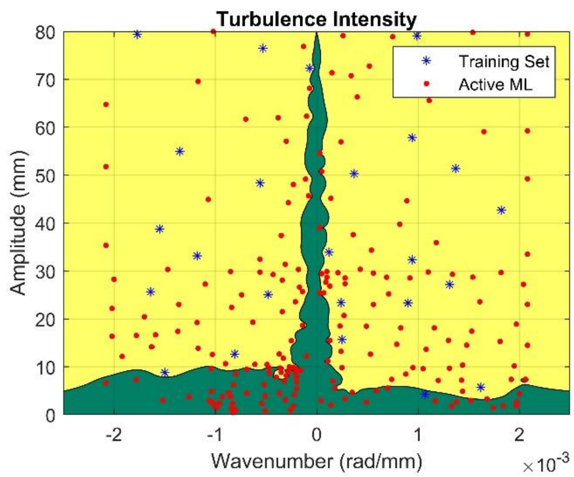


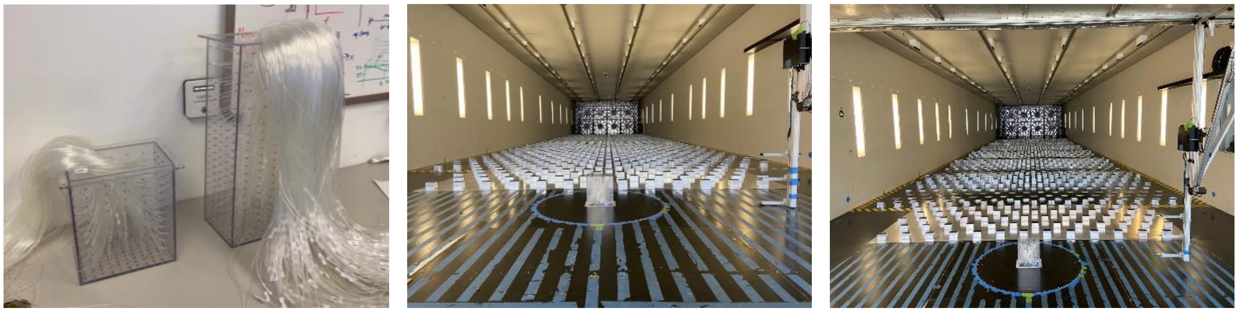
Figure 2. Parameter space

3. MEASSURING PRESSURES ON BLUFF BODIES

The next step was to investigate the effect of the non-Gaussian turbulence on the peak pressure coefficients measured on bluff-bodies (Figure 3.a). The two models have identical simple rectangular plan geometry and heights 250 mm and 500 mm. Each model was first tested with 26 repetitions using the baseline 80 mm element configuration (Figure 3.b) to establish the baseline pressure and its uncertainty bounds. The benchmark test was repeated 13 times from 0 to 180 degrees in increments of 15 degrees, then by tap symmetry it was possible to obtain the 26 time histories to statistically determine the peak pressure coefficients, $\hat{C}_p$ for the benchmark.

Once the Benchmark experiment data was collected, several Terraformer configurations with different outcomes for second-order and higher-order profile characteristics were used to test the models at 0 to 90 degrees in increments of 15 degrees. The data was collected with a 512 TCU

Scanivalve system for a duration of 2 min per direction. Once the pressure was recorded, the C_p^{peak} was computed for each tap for analysis.



a) 250 mm and 500 mm tall models

b) Benchmark Terraformer configuration

c) Single harmonic Terraformer configuration

Figure 3. Bluff body experiments

We have begun to define statistically the $\hat{C}_p$ of the benchmark experiment as well as the equivalency criteria. Once the equivalency criteria are defined, model pressures from the different Terraformer configurations will be compared to the benchmark pressure. We expect to complete this phase by early summer 2023 and be prepared to discuss findings and implications regarding peak pressure coefficients at the ICWE.

4. FINDINGS AND IMPLICATIONS

To date, studies have been carried out for several Terraformer parameterization schemes. The integrated experimental procedure has successfully collected profiles for 1198 unique roughness configurations over a period of 480 hours. Without ML, an estimated ~10x more experiments would be necessary to evaluate the hypothesis. In the case of the bluff body experiments, the 250 mm and 500 mm height models have been tested for 32 and 64 Terraformer configurations respectively, in addition to the 26 benchmark experiments. The data collected from the experiments is being curated for publication in the NHERI DesignSafe Data Repository.

ACKNOWLEDGEMENTS

This material is based upon work supported by the National Science Foundation under grants CMMI 1930389 & 1930625. The University of Florida shared use NHERI experimental wind facility was utilized for all wind tunnel experiments (Grant No. 2037725). The dedication of the support staff at the UFBLWT is gratefully acknowledged.

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