## **Equivalent Turbulence Profiles from Randomized Terrain** in a Boundary Layer Wind Tunnel

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## 1. BACKGROUND AND MOTIVATION

This ongoing research project (CMMI 1930389 & 1930625) investigates whether commonly achieved matching of first and second order turbulence profiles in 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 differing higher-order properties that may produce non-equivalent peak loads. Outcomes include the potential identification of a source of uncertainty among multi-facility studies of like subjects, and identifying the limitations of constraining the definition of approach turbulence to second order metrics.

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' - Fig. 1) and instrument gantry are integrated with an active machine learning

algorithm that chooses the next roughness element configuration to investigate based upon an objective and the accumulated outcomes of every previous experiment.

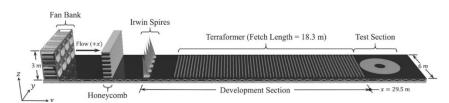


Figure 1. UFBLWT configuration

## 2. METHODOLOGY

Part I Benchmark Profile: A homogeneous baseline terrain was first established as 8 cm height for each of the 1116 roughness elements. An automated gantry system was used to move 3 cobra probes to predetermined locations within a measurement plane to quantify the wind field and establish a benchmark second order profile. This was repeated 25 times to refine the benchmark and to quantify acceptable error bounds among the 25 identically run experiments, i.e. define 'statistically equivalent' second order profiles.

Part II 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 machine learning 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 second 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 machine learning algorithm for part III.

Part III Active Machine Learning: The training experiments informed the initial conditions of an active machine learning algorithm that was tasked with finding the regions of the Terraformer parameter space that produce profiles statistically equivalent to the benchmark profile. This combination of automated instrumentation, parameterized Terraformer, and active machine learning algorithm was then turned loose, where the next experiment (next Terraformer configuration) was determined by the machine learning algorithm. The goal was to identify the region, within the two-parameter space, of equivalent second order behavior, and then probe this region for higher order differences (part IV). After a sufficient number of configurations are conducted, the equivalent second-order parameter space emerges. Figure 2 illustrates the two parameter space, where the equivalent second order region is the green area, and the non-equivalent second order region is the yellow area. In the figure, the blue stars indicate the Part II Training Set, and the red dots the Part III Active Machine Learning experiments.

Part IV Higher-Order Investigation: Part III identified a continuum of Terraformer configurations that produce turbulence profiles that statistically are indistinguishable with respect to second order characteristics (e.g. Fig. 2). We have begun to explore this space for higher order characteristics that may differ within the second order equivalent region. Results are premature at this date, but we expect to complete this phase by early spring 2022 and be prepared to discuss findings and implications regarding peak pressure coefficients at the ACWE.

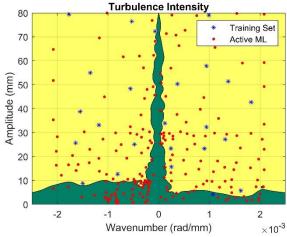


Figure 2. Parameter space

## 3. FINDINGS AND IMPLICATIONS

To date, studies have been carried out for three different Terraformer parameterization schemes (single harmonic, square and saw tooth, and Karhunen-Loeve Expansion). Between them, the integrated Terraformer, gantry and adaptive learning experimental procedure has been successfully conducted for 861 unique element roughness configurations over a period of 340 hours. Establishing the second order equivalent zone without the learning algorithm would require ~10x more experiments, which would push the current discoveries beyond reach. The latest results and implications will be presented during the ACWE. The data collected from the experimental procedure is being curated for publication in the NHERI DesignSafe Data Repository within the next 12 months.