Active Machine Learning in Large Scale Wind Tunnel Experiments

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ABSTRACT:
Boundary Layer Wind Tunnel (BLWT) facilities are commonly used for assessing wind loads on structures. Although BLWT facilities routinely match 1st and 2nd-order wind field models, evidence suggests that turbulence 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 in order to identify differing profiles with equivalent second-order equivalent flow. The premise is that second-order equivalent wind fields can differ in higher-order properties and therefore extreme value derived peak loads.

Keywords: Boundary Layer Wind Tunnel, Adaptive Learning, Machine Learning, peak wind loads

1. BACKGROUND AND MOTIVATION

This ongoing NSF sponsored research project (CMMI 1930389 & 1930625) investigates whether commonly achieved matching of first and second order wind field properties in BLWT flow is sufficient for producing consistent expected value peak wind pressures. We hypothesize that multiple roughness element configurations can produce equivalent second-order wind fields, but impart different higher-order properties and therefore different peak load metrics derived from extreme value analysis. Despite this widely recognized open question, such investigations have been limited in the past due to a lack of both suitable facilities to accommodate a large number of terrains and a means of rapidly informing and changing the test matrix between experiments.

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 and instrument gantry are integrated with a machine learning algorithm that chooses the next roughness configuration to investigate based upon 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 parameter subspace that corresponds to second order equivalent boundary layer profiles. The next phase will then investigate the higher-order characteristics of this second-order equivalent subspace.

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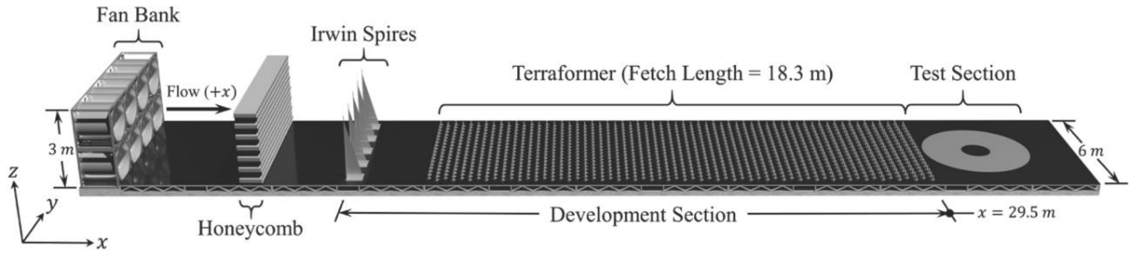

Figure 1. UFBLWT configuration

The University of Florida Boundary Layer Wind Tunnel (Fig. 1) offers a unique automated terrain roughness element system (Terraformer) which can independently reconfigure each of 1116 individual elements in less than 90 seconds (Catarelli et al. 2020). Three vertically aligned turbulence measuring Cobra probes are mounted on an automated articulating gantry (Fig. 2) programmed to move in three dimensions. In this manner, vertical turbulence profiles are measured during each experiment. This shared use facility is accessible through the NSF sponsored Natural Hazards Engineering Research Infrastructure (NHERI) program (CMMI 1520842 & 2037725).

2. METHODOLOGY

Two different wind profiles, produced by any pair of roughness element configurations 'a' and 'b', are considered second order equivalent if the turbulence intensity profiles in u (longitudinal) wind direction are equal in a statistical sense within the inertial sublayer and satisfy:

$$d(\boldsymbol{x},\boldsymbol{x}^*) = \|I_u(\boldsymbol{x}) - I_u(\boldsymbol{x}^*)\|_2 \tag{1}$$

In Eq. (1), the distance metric ($d(\boldsymbol{x},\boldsymbol{x}^*)$) of two different profiles is defined. $I_u(.)$ is the turbulence intensity profile in u direction, $\boldsymbol{x}$ and $\boldsymbol{x}^*$ are different Terraformer configurations. This equivalence metric is used to inform the learning algorithm that adaptively explores the bounded two-parameter Terraformer domain to identify second-order equivalent configurations. The approach in this study exploits the Adaptive Kriging-Monte Carlo Simulation (AK-MCS) (Echard et al. 2011) algorithm with a modified U learning function applied to the profile distance measure. Gaussian Process (GP) Regression is a non-parametric Bayesian approach to construct a surrogate model that, in our case, predicts the distance between two profiles and the associated prediction uncertainty at new (untested) terraformer configurations. The learning function then selects new Terraformer parameters based on the existing test data with the goal of identifying Terraformer configurations that produce second-order equivalent profiles.

Fig. 2 illustrates the main framework of this study. A semi-automated approach is adopted, where the adaptive learning portion is automated, and the user has full control over the wind tunnel experimental procedure. The framework begins by conducting a benchmark experiment against which second-order equivalence will be measure. A small number of initial experiments are conducted by sampling from the Terraformer parameters, the distance from the benchmark is computed, and these distances serve as training data to fit the GP regressor. The defined learning function selects a new sample and defines the next Terraformer configuration for the user to initialize the experiment and data collection. Following the experiment, the resulting profile is automatically collected, the distance from the benchmark computed, the GP surrogate model is updated, learning function evaluated and a new test initiated.

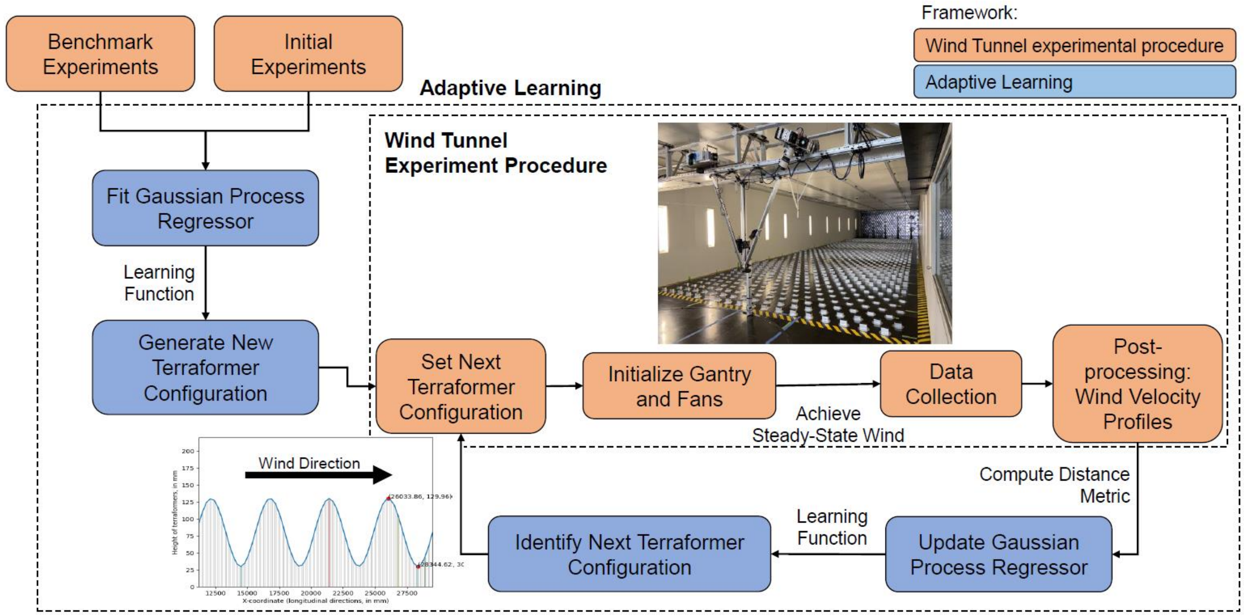

Figure 2. Flowchart of the adaptive learning based experimental procedure

3. CURRENT STATUS

The integrated Terraformer, gantry and adaptive learning experimental procedure has been successfully conducted for 287 element roughness configurations over a period of four weeks. The latest results and implications will be presented during the workshop. Currently, the data collected from the experimental procedure is being curated for publication in the NHERI DesignSafe Data Repository within the next 12 months.

ACKNOWLEDGEMENTS

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