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Active Machine Learning in Large Scale Wind Tunnel Experiments

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1. BACKGROUND AND MOTIVATION

Optimal design of experiments aims to reduce the expensive experimental time by minimizing the number of required experiments. Machine learning methods provide a wide range of capabilities to learn from available data and make informed experimental design decisions. This kind of adaptive approach can focus experiments on estimating certain quantities of interest and converge to accurate results using a small number of experiments. This makes active learning very attractive for large scale experimental setups such as the Boundary Layer Wind Tunnel (BLWT). High-throughput BLWT experiments are time consuming, thus it is necessary to select each sample carefully. In this project, we control the automated "Terraformer" – an automated roughness grid – at the University of Florida BLWT to learn the influence of random field roughness conditions on wind flow statistics. Specifically, an active machine learning framework is employed to identify relationships between stochastic roughness element configurations and statistical properties of the generated wind fields.

This ongoing NSF research project (CMMI 1930389 & 1930625) explores the stochastically generated terraformer roughness grids to identify second-order statistically equivalent configurations. We further investigate the variation of higher-order statistical properties (e.g., extreme velocities) among second-order equivalent wind fields. The active learning process is enabled by two automated tools unique to the UF-BLWT: the Terraformer roughness grid (Fig. 1) and a Gantry system capable of collecting velocity measurements throughout the tunnel. Together these elements enable high-volume throughput experiments and rapid data collection for on-

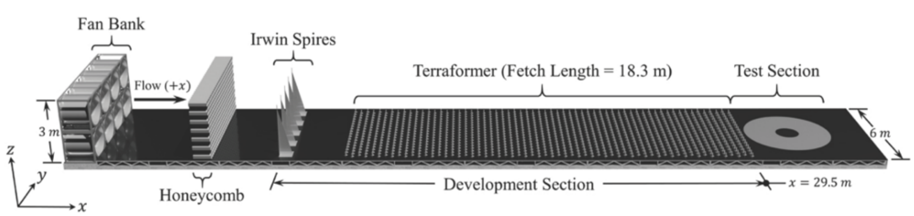

Figure 1. University of Florida BLWT.

the-fly processing and active learning.

2. METHODOLOGY

The primary objective of this study is to identify stochastic field roughness element configurations that generate 2^{nd}-order statistically equivalent wind profiles. The roughness terrain is parameterized by a Karhunen-Loeve (KL) expansion that describes possible stochastic roughness configurations having a specified correlation function. Within the space of KL random variables, we identify the subspace that contains 2^{nd}-order equivalent wind fields. The 2^{nd}-order difference between two wind profiles, generated by different roughness configurations, is given by:

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

where $I_u(.)$ is the longitudinal turbulence intensity profile for terraformer configurations having KL parameters $\boldsymbol{\theta}$ and $\boldsymbol{\theta}^*$. Two profiles are considered 2^{nd}-order equivalent if $d(\boldsymbol{\theta}, \boldsymbol{\theta}^*)$ is below a prescribed tolerance.

The active learning algorithm adaptively explores the KL parameters of the Terraformer grid using a Gaussian process regression surrogate to approximate the distance between wind profiles and a modified U-learning function adapted from the Adaptive Kriging-Monte Carlo Simulation (AK-MCS) (Echard et al. 2011) algorithm that is widely used for reliability analysis. Fig. 2 illustrates the full semi-automated framework, which will be described in detail in the presentation.

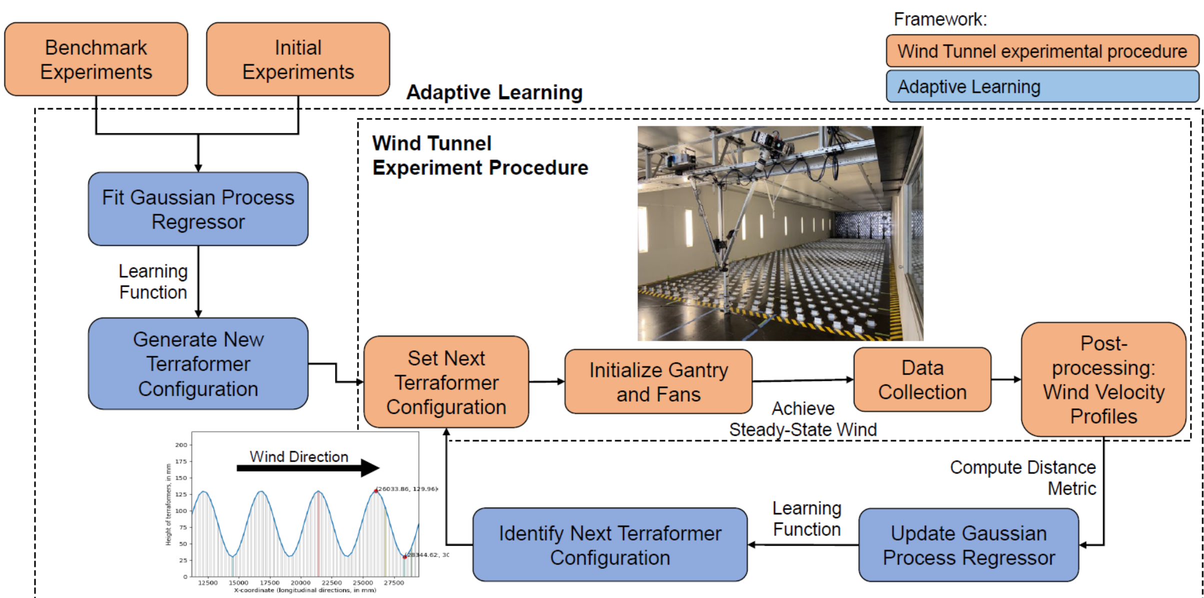

Figure 2. Flowchart of the adaptive learning based experimental procedure

3. CURRENT STATUS

The integrated Terraformer, gantry and active learning experimental procedure has been employed to conduct 861 unique experiments with machine learned element roughness grids over a period of 340 hours. The latest results will be presented to illustrate regions of the KL parameter space for roughness grids that correspond to 2^{nd}-order equivalent profiles and the sensitivity of these distance measure to these parameters. Data collected from these experiments will be presented and are being curated for publication in the NHERI DesignSafe Data Repository.