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DRDMannTurb: A python package for scalable, data-driven synthetic turbulence

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Software

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Summary

Synthetic turbulence models (STMs) are used in wind engineering to generate realistic flow fields and employed as inputs to wind simulations. Examples include prescribing inlet conditions and inflow wind fields to model loads on wind turbines and tall buildings. We are interested in STMs capable of generating fluctuations based on prescribed second-moment statistics as this allows for simulating environmental conditions closely resembling on-site observations. To this end, the widely used Mann model (Mann, 1994, 1998) is the inspiration for `DRDMannTurb`. Three physical parameters describe turbulence in this model: a magnitude parameter corresponding to the Kolmogorov constant multiplied by the rate of viscous dissipation of the turbulent kinetic energy to the two thirds, $\alpha\epsilon^{2/3}$, a turbulence length scale parameter L, and a non-dimensional parameter Γ related to the lifetime of the eddies. A number of studies as well as international standards (e.g., the International Electrotechnical Commission) include recommendations for values of these three parameters with the goal of standardizing wind simulations to realistic energy spectra. Yet, having only three parameters, the Mann model faces limitations in accurately representing the diversity of observable spectra. This Python package allows users to extend the Mann model and more accurately fit field measurements through a neural network model of the eddy lifetime function. Following (Keith et al., 2021), we refer to this class of models as deep rapid distortion (DRD) models. Once calibrated, a DRD model is no more expensive for simulating turbulence than a Mann model. Moreover, `DRDMannTurb` comes with a state-of-the-art domain decomposition-based simulator for generating turbulence boxes for both Mann and DRD models.

Statement of need

`DRDMannTurb` aims to create an easy-to-use framework to (1) fit one-point spectra from data using the DRD model introduced in (Keith et al., 2021) and (2) to efficiently generate synthetic turbulence velocity fields to be used by scientists and engineers in downstream tasks. Existing methodologies for generating synthetic turbulence frequently incur a large computational overhead and lack the DRD model's flexibility to represent the diverse spectral properties of real-world observations, cf. (Liew, J., 2022). `DRDMannTurb` addresses these two issues by introducing (1) a module for fitting neural network-based DRD models to observed one-point spectra data as well as (2) a module for efficiently generating synthetic turbulence boxes. Rather than generating turbulence for the entire box at once, a highly memory-intensive practice used in other software, `DRDMannTurb` uses a state-of-the-art domain decomposition approach to generate smaller sub-boxes sequentially.

`DRDMannTurb` is completely written in Python, leveraging computationally powerful backend packages (`numpy`, `PyTorch`). Our implementation allows for easy GPU-portability using `cuda`. This is an additional advantage compared to previously developed software packages that have implemented the Mann model but do not provide the source code (e.g., HAWC2). Finally, DRDMannTurb is designed to be more general-purpose, allowing it to be applied to a broader range of scenarios, as well as be more accessible and with clear documentation for a variety of tasks that researchers in this area frequently use.

Results

The output of the fitting component of DRDMannTurb consists of two parts: the spectra fit by a DRD model and the learned eddy lifetime function. For example, in the case of a Kaimal spectra, the DRD spectra fit is more accurate than that of the Mann uniform shear model while providing an estimate of the physical parameters.

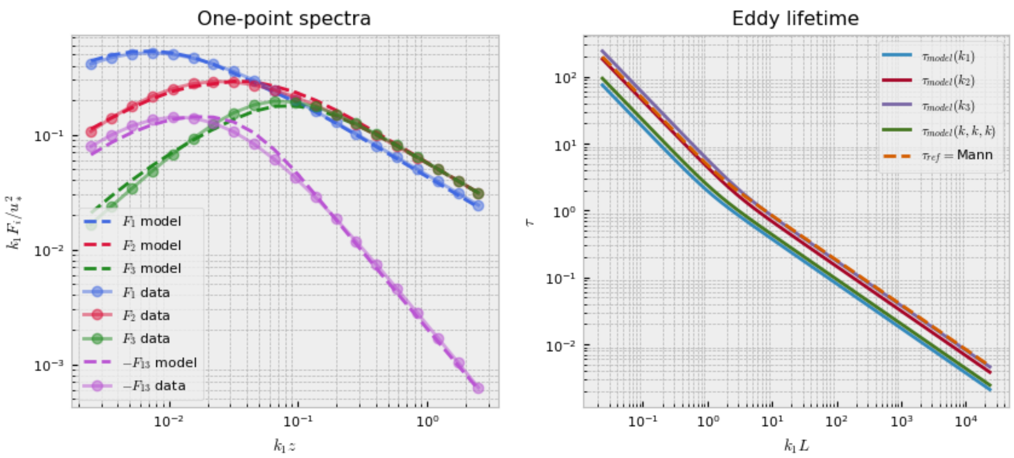

Figure 1: Synthetic DRD Model Fit

After fitting to the spectra, the resulting models can also be used to generate 3D wind fields with spectra more closely resembling the same observations used in training.

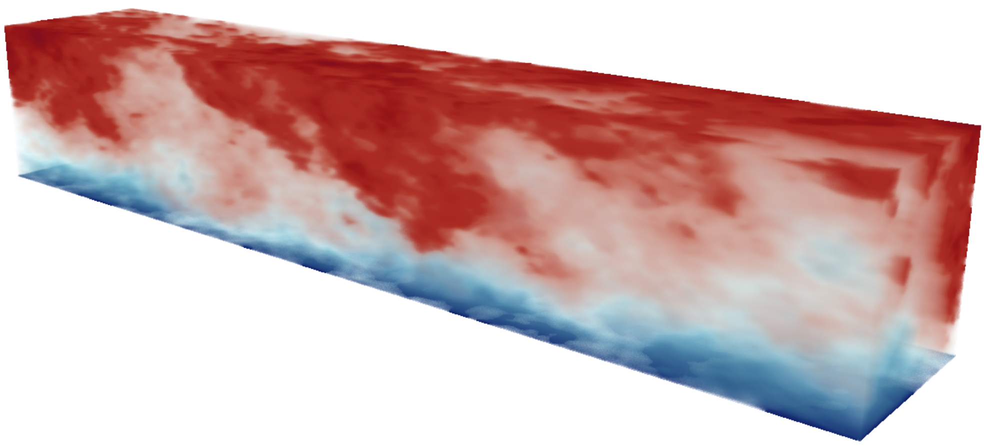

Figure 2: Simulated Wind Tunnel

For more detailed discussions of results, including a variety of utilities for interpolating and filtering noisy real-world data and generating wind turbulence, please see the official examples.

Package Features

- Calibrate the Mann model parameters using reference “textbook” or in-situ spectra and co-spectra
- Calibrate the DRD model using a flexible suite of neural network architectures for the eddy lifetime functions
- Generates synthetic turbulence fields using the classical Mann model
- Fast synthetic turbulence generation using a state-of-the-art domain decomposition approach

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