

# 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 are employed as inputs to industrial wind simulations. Examples include prescribing inlet conditions in large eddy simulations that model loads on wind turbines and tall buildings. We are interested in STMs capable of generating fluctuations based on prescribed second-moment statistics since such models can simulate environmental conditions that closely resemble on-site observations. To this end, the widely used Mann model (see [Mann, 1994, 1998](#)) is the inspiration for DRDMannTurb. The Mann model is described by three physical parameters: a magnitude parameter influencing the global variance of the wind field and 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  $\Gamma$  related to the lifetime of the eddies. A number of studies, as well as international standards (e.g., those by the International Electrotechnical Commission (IEC)), include recommended values for these three parameters with the goal of standardizing wind simulations according to observed energy spectra. Yet, having only three parameters, the Mann model faces limitations in accurately representing the diversity of observable spectra. This Python package enables users to extend the Mann model and more accurately fit field measurements through flexible neural network models of the eddy lifetime function. Following Keith et al. ([2021](#)), we refer to this class of models as Deep Rapid Distortion (DRD) models. DRDMannTurb also includes a general module implementing an efficient method for synthetic turbulence generation based on a domain decomposition technique. This technique is also described in Keith et al. ([2021](#)).

## Statement of need

DRDMannTurb aims to provide 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) 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 DRD models' 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 DRD models to observed one-point spectra data, as well as (2) a module for efficiently generating synthetic turbulence boxes. Rather than generating turbulence over an entire domain at once, which can end up being a highly memory-intensive practice, DRDMannTurb uses a domain decomposition approach to generate smaller sub-boxes sequentially.

DRDMannTurb is written in Python and leverages computationally powerful backend packages like NumPy and PyTorch. The implementation makes DRD models easily portable to GPU

and other backends via PyTorch. This is an additional advantage compared to other software packages that implement the Mann model, but for which the source code may not be public or freely available (e.g., HAWC2 (Madsen et al., 2020)). Finally, DRDMannTurb is designed to be more general-purpose, allowing it to be applied to a broader range of scenarios and to be very accessible, with clear documentation and examples spanning a variety of tasks that researchers may be interested in.

## 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 the Kaimal spectra, the DRD spectra fit is more accurate than the Mann uniform shear model while providing an estimate of the same three physical parameters.

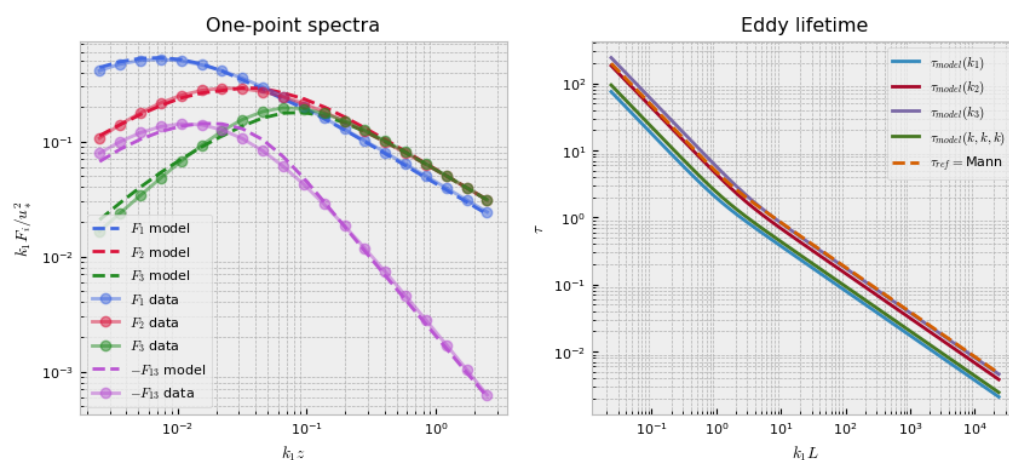


Figure 1: DRD model fit to the Kaimal spectra.

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.

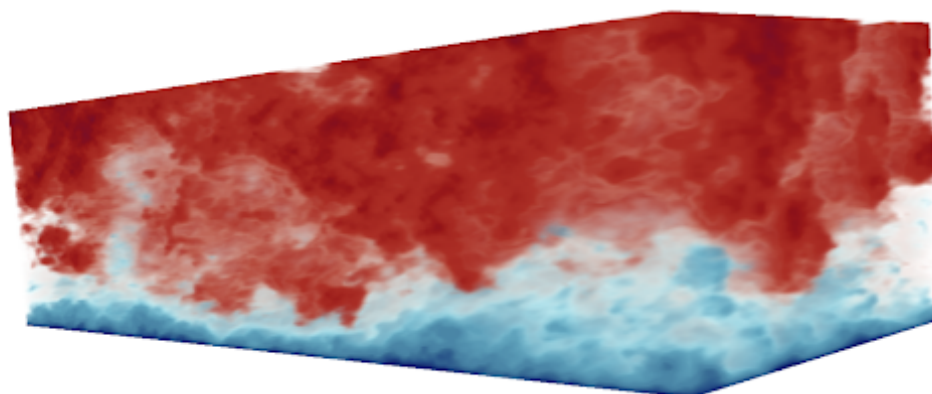


Figure 2: Synthetic wind field.

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
- Generate synthetic turbulence fields using the classical Mann model
- Use a state-of-the-art domain decomposition approach for fast synthetic turbulence generation

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