The Journal of Open Source Software

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

Alexey Izmailov[1], **Matthew Meeker**[1], **Georgios Deskos**[2], and **Brendan Keith**[1]

1 Division of Applied Mathematics, Brown University, Providence, RI, 02912, USA **2** National Wind Technology Center, National Renewable Energy Laboratory, Golden, CO, 80401, USA

DOI: 10.21105/joss.06838

Software

- Review
- Repository
- Archive

Editor: Rohit Goswami

Reviewers:

- @paroomk
- @olivecha

Submitted: 19 March 2024
Published: 15 October 2024

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 (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 Γ 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

The Journal of Open Source 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.

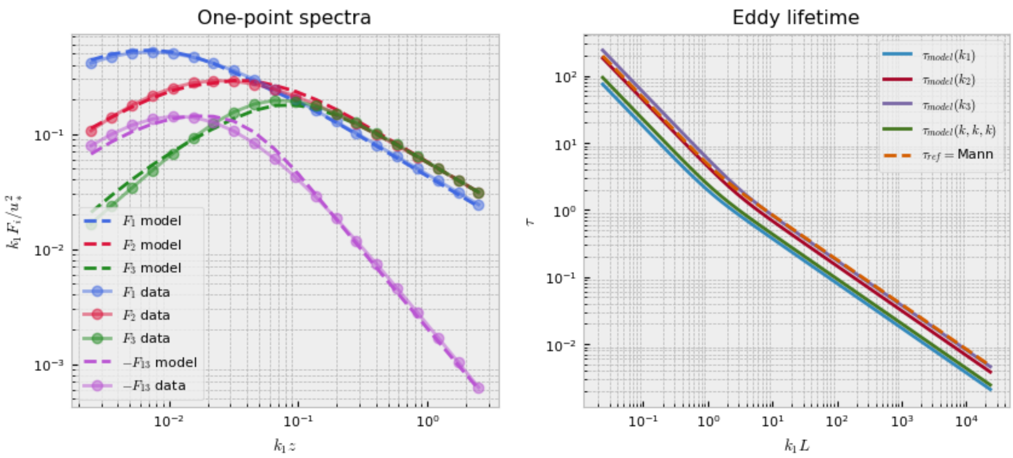

Figure 1: DRD model fit to the Kaimal spectra.

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.

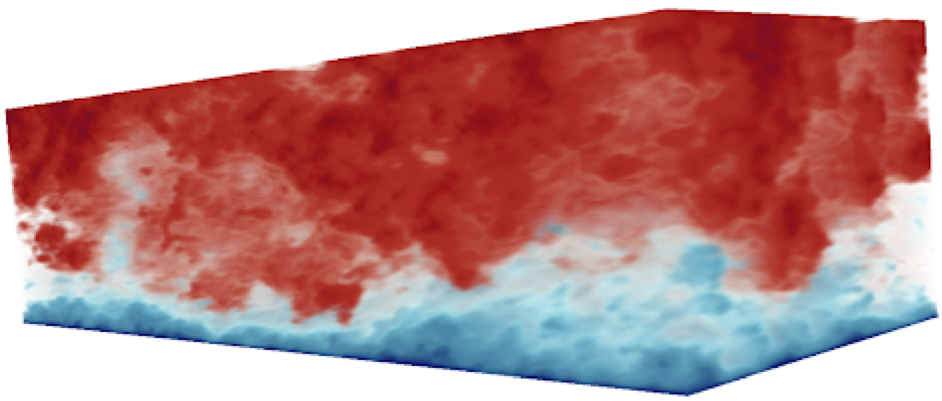

Figure 2: Synthetic wind field.

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

Acknowledgements

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Wind Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes. BK was supported in part by the U.S. Department of Energy Office of Science, Early Career Research Program under Award Number DE-SC0024335.

References

Keith, B., Khristenko, U., & Wohlmuth, B. (2021). Learning the structure of wind: A data-driven nonlocal turbulence model for the atmospheric boundary layer. *Physics of Fluids*, *33*(9). https://doi.org/10.1063/5.0064394

Liew, J. (2022). *Mann.rs* (Version 1.0.0). https://doi.org/10.5281/zenodo.7254149

Madsen, H. A., Larsen, T. J., Pirrung, G. R., Li, A., & Zahle, F. (2020). Implementation of the blade element momentum model on a polar grid and its aeroelastic load impact. *Wind Energy Science*, *5*, 1–27. https://doi.org/10.5194/wes-5-1-2020

Mann, J. (1994). The spatial structure of neutral atmospheric surface-layer turbulence. *Journal of Fluid Mechanics*, *273*, 141–168. https://doi.org/10.1017/S0022112094001886

Mann, J. (1998). Wind field simulation. *Probabilistic Engineering Mechanics*, *13*(4), 269–282. https://doi.org/10.1016/S0266-8920(97)00036-2