Predicting volatile wind energy

Stochastic forward modeling and machine learning

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Motivation

Forecasting power output from wind farms is a standing challenge due to complex dynamical processes in the turbulent **Atmospheric Boundary Layer (ABL)** that manifest themselves by a a notable **spatio-temporal variability of the wind**. Predictions for single turbines considering ABL processes are generally not possible. Here, we show a way to achieve such predictions based on an **economical stochastic forward model** that autonomously evolves vertical profiles of the wind velocity and temperature.

Main objectives

- **Short-term prediction** of site-specific **wind speed fluctuations** governing volatility of wind energy
- Physics-based **stochastic forward modeling**
- **Clustering analysis** of turbulence events and time series for **various flow conditions**

Reduced order stochastic forward modeling

Fig. 1 shows the setup for application of the model, and the model rationale for the representation of turbulent transport by velocity fluctuations (turbulent advective transport). Vertical profiles of momentary wind velocity and temperature profiles are evolved in time for any given site (location) and initial condition by the stochastic **One-Dimensional Turbulence (ODT) model** [1] . ODT is a reduced order model which aims to represent the effects of 3-D turbulence along a 1-D physical coordinate (a vertical line of sight pointing in vertical z direction). This is achieved by spatial mappings that punctuate deterministic diffusive advancement processes and wind veering effects due to Coriolis forces in the stratified **Atmospheric Boundary Layer (ABL)** [2, 3]. The model reduction strategy implies **major cost reduction** making parametric studies [3, 4, 5] and real-time predictions feasible. The model representation of overturning turbulent motions (eddies) consists of **turbulent baker's maps** [6, 7], enabling accurate and economic representation of wind fluctuations across wind turbines.

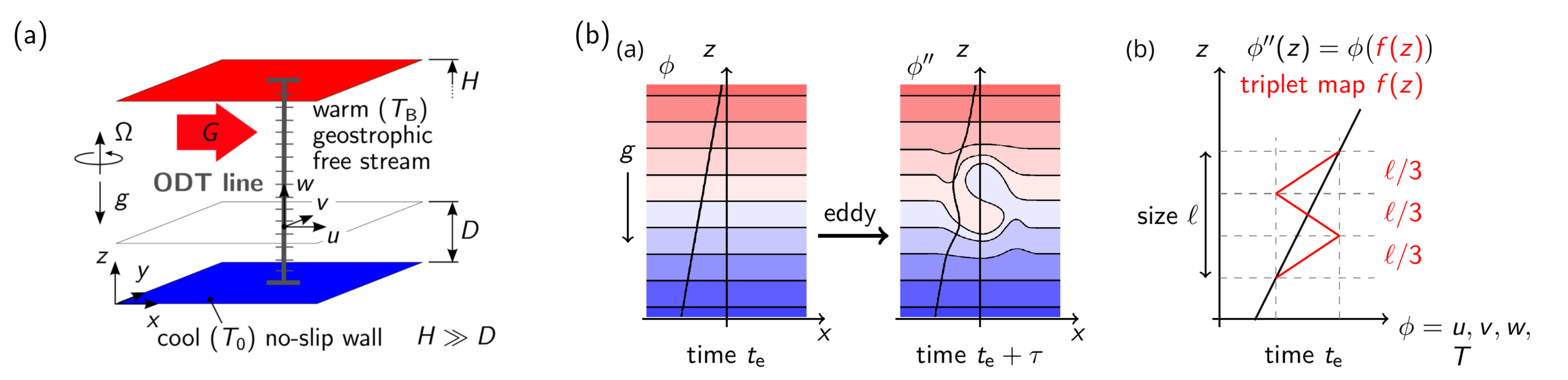

Figure 1: (a) Sketch of the idealized ABL and the orientation of the reduced order flow domain (ODT line). H is the height of the ODT line, $D = \sqrt{2\nu/f}$ the Ekman boundary layer length scale, $f = 2\Omega$ is the Coriolis parameter and Ω the angular velocity of a co-rotating frame of reference. G is the geostrophically balanced free stream velocity that acts as momentum reservoir. T_0 is the temperature of the cooled smooth surface and $T_B > T_0$ the bulk temperature. (b) Model representation of a turbulent eddy. The effect of stretching and folding of vortex lines is represented in ODT by triplet map $f(z)$ applications. Figures are reproduced from [3].

Labeled data from event-based decomposition

The dynamical complexity of ODT together with the emergence of multiple time and length scales in the ABL yield **large amounts of data** that contain flow-physical information. **Fig. 2(a)** shows the evolution of an idealized daytime (Fr $= 1000$) and nighttime (Fr $= 10$) ABL in terms of different flow variables together with the **sequence of stochastically sampled eddy events** (blue bars in bottom panel) as **labeled model output**. **Fig. 2(b)** shows the size, position and dissipation associated to model implemented mappings. Latter is convenient since readily available in the reduced order model, but could be obtained also from measurements or high-fidelity numerical simulations by reduction through filtering or machine learning algorithms (like modal decompositions based on empirical orthogonal functions [8], among other approaches).

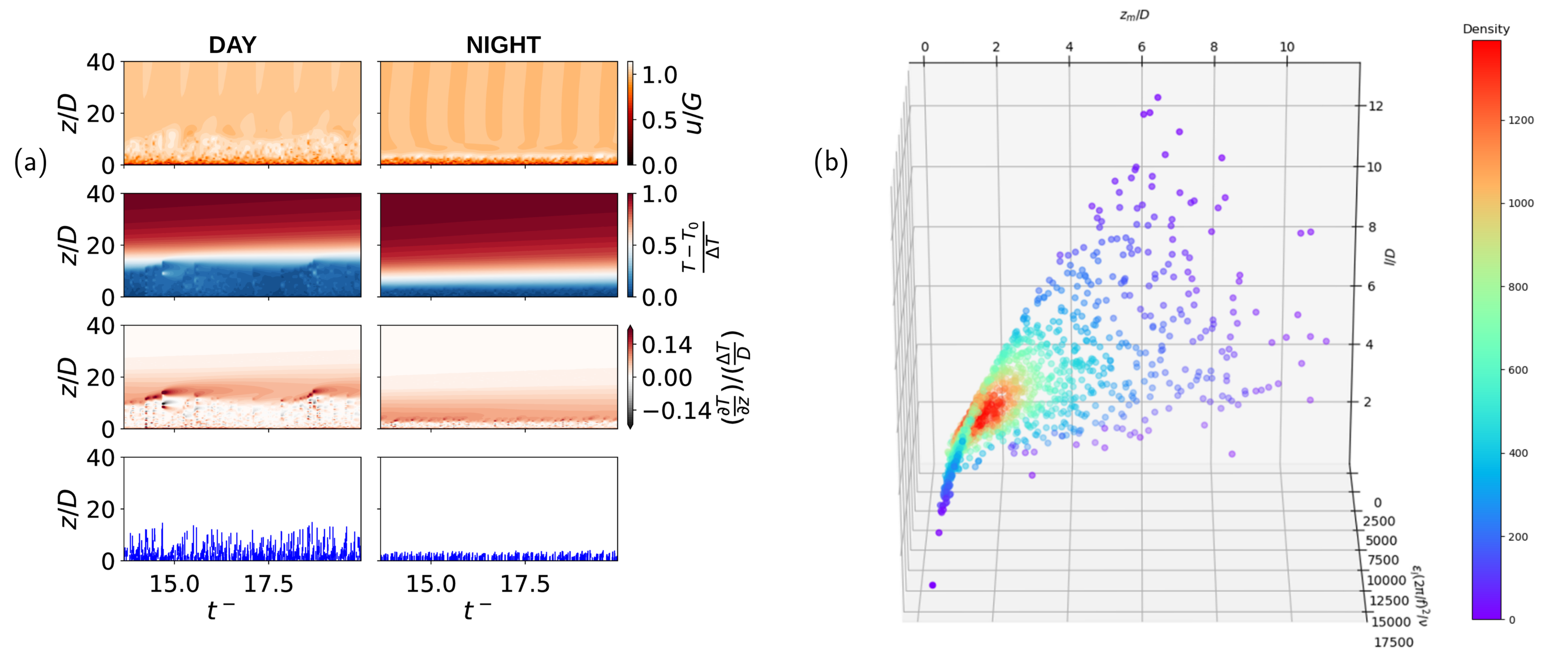

Figure 2: (a) Space-time diagram of two stochastic ODT simulations of an idealized daytime (Fr $= 1000$, weakly stable) and nighttime (very stable, Fr $= 10$) atmospheric boundary layer (Re $= 500$). Note that Fr $= G^2/(g\,D\,\beta\,\Delta T)$, where $\beta = T_{\text{ref}}$ is the coefficient for linearized thermal expansion of air as an ideal gas at reference temperature T_{ref} (Oberbeck–Boussinesq limit for buoyant flow). Figure reproduced from [3]. (b) Scatter plot showing the size, position, and kinetic energy dissipation of stochastically sampled triplet maps for the daytime ABL (colors encode the kernel density of implemented mappings).

Data analysis using machine learning algorithms

Machine Learning (ML) algorithms are versatile but require appropriate data. ODT eddy events are a convenient choice since they represent **physically labeled data** (size, location and time of occurrence, available energy, among other eddy properties). **Fig. 3** and **Fig. 4** show the segregated ODT eddy event sequence due to **time–midpoint clustering** of mappings using **DBSCAN** [9] and **OPTICS** [10], respectively. The inertial period $2\pi/f$ and the corresponding laminar Ekman boundary layer thickness D are only used to scale the axes, but are not used for clustering in order to retain most weight on temporal proximity. Each eddy event was shifted by half of its eddy turnover time to remove the forward-in-time bias for ODT eddy event data when utilizing a simple Euclidean norm. Successful application of the clustering algorithms also mandated careful normalization time and location, here by scaling with reference length D and reference velocity G.

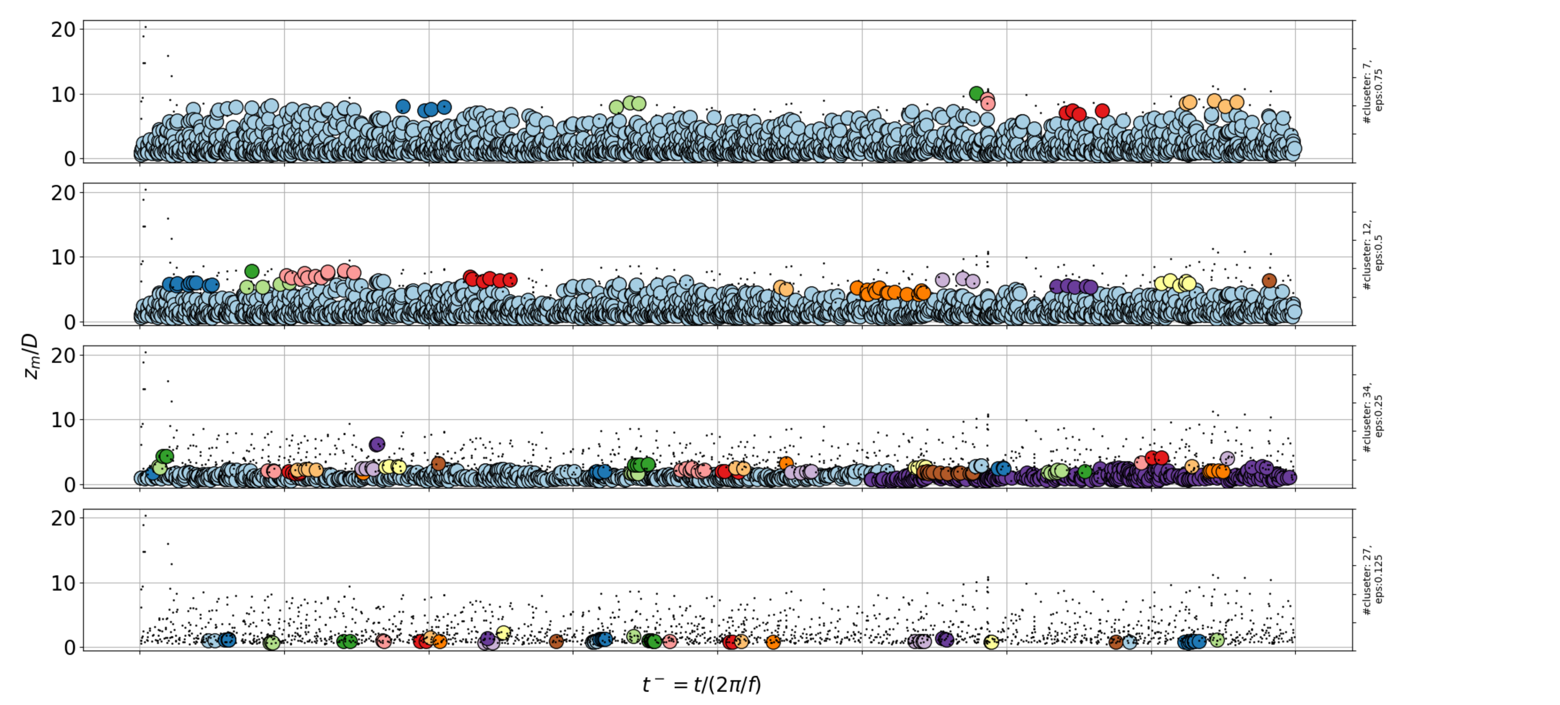

Figure 3: DBSCAN clustering algorithm applied to physically labeled ODT eddy events selecting different values of the (dimensionless) ε-ball radius. Different values of ϵ result in different clusters that separate eddy events by a mixing length criterion.

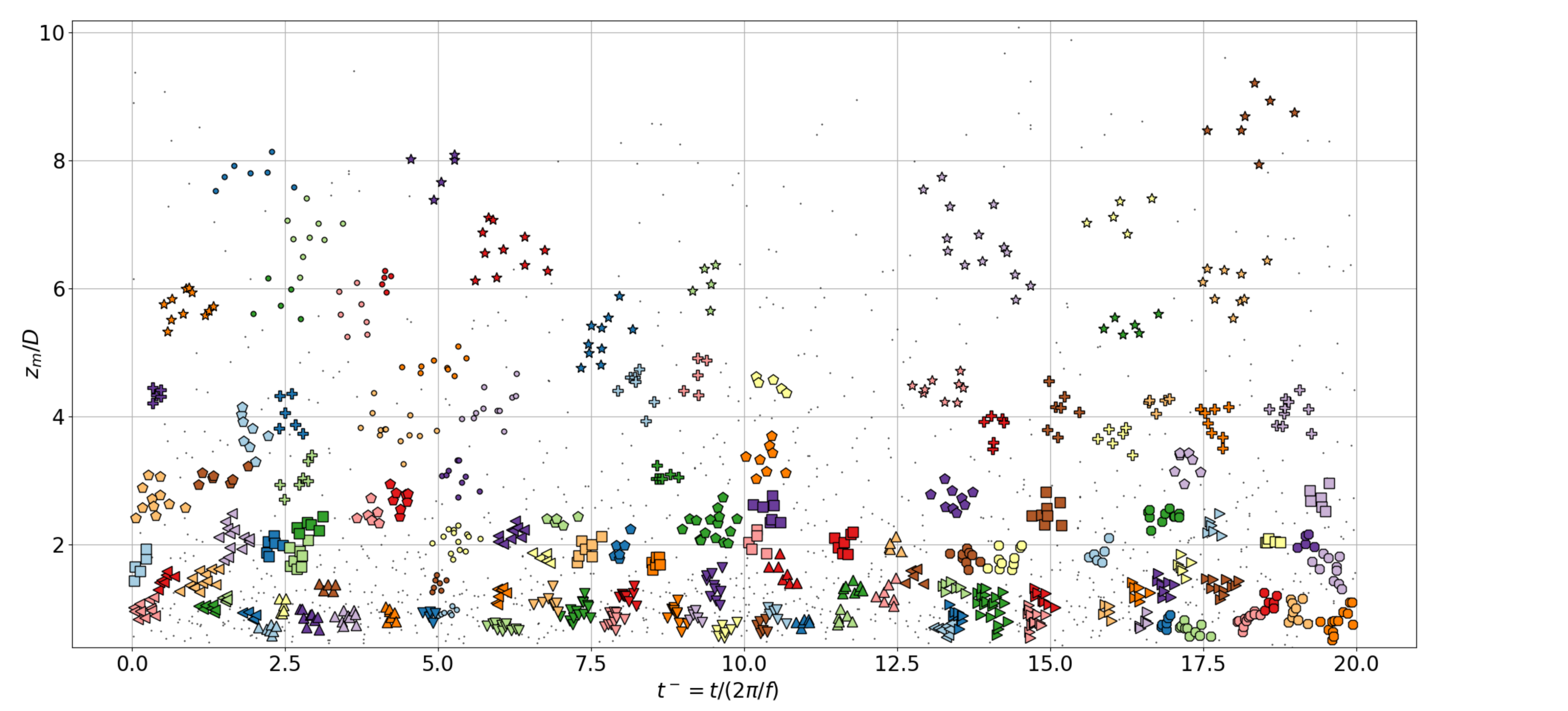

Figure 4: OPTICS clustering algorithm with automatic adjustment of the ε-ball radius applied to physically labeled ODT eddy events. Distinctive causal clusters have been identified, visualized by varying the marker and color combination.

Multiscale features of turbulent fluctuations and intermittency

Fig. 5(a) shows a number of clusters, each with a different color, providing a 'bare-bone' perspective on **cascading effects** and **intermittency** (qualitatively) in a temporally developing ODT solution.

Model output can also be analyzed by means of conventional statistics. A time-dependent streamwise velocity signal located at $z/D = 10$ above the surface for the well-mixed near-neutral daytime simulation case (Fr $= 1000$, Re $= 500$). In practice, this provides the **stochastically modeled time-series of the fluctuating wind speed at hub height**. Last, **Fig. 5(b)** shows the results of a seasonal-trend decomposition procedure on the time-dependent model-generated streamwise velocity signal. The seasonal decomposition utilizes the inertial period ($2\pi/f$) as an input. It is noted how larger frequencies and more intricate seasonal components are present due to a rare but intense, **highly dissipative mixing event** that involves an eddy cascade across scales and is representative of intermittency effects.

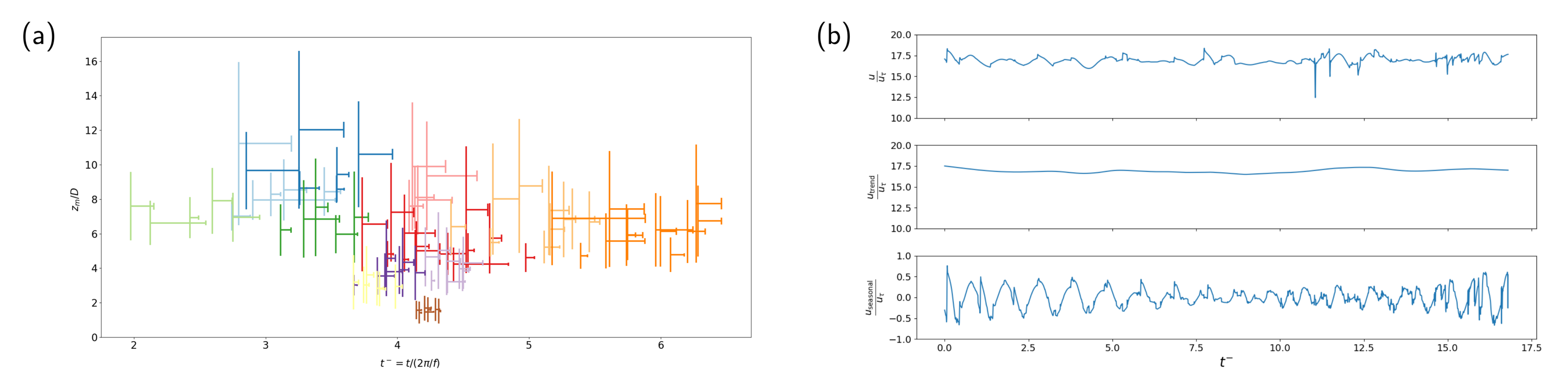

Figure 5: (a) Zoom of an OPTICS-based cluster based on eddy time of occurrence and eddy midpoint location. Each color marks a different out of a couple consecutive clusters. Vertical lines denote the eddy event size. The center of the vertical lines is the eddy midpoint position (b) Seasonal-trend decomposition for a model generated time-dependent streamwise velocity signal at $z/D = 10$ above the surface.

Conclusions

- **Volatility** is a crucial aspect of next generation energy systems, in particular, due to **wind fluctuations**.
- **Multiscale modeling** strategies with **predictive capabilities** are needed in order to proceed towards **real-time analysis** and **short-term forecasting** of **wind farm power output**.
- The combination of **stochastic** and **machine-learning-based modeling** approaches addresses predictability and efficiency aspects.

Forthcoming research

- Realistic turbulence intensities (high Reynolds number flow)
- Coupling of ODT with blade and turbine models
- Incorporation of measured data and automated restart
- Stochastic deconvolution for detailed short-term power output forecasting

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