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Simulating Volatile Wind Energy

Stochastic Forward Modeling and Machine Learning

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Keywords:
- Data analysis
- Reduced order modeling
- Transfer

Motivation

The transformation of the energy sector is based on the integration of various renewable sources, such as wind and solar energy. One of the key challenges for the integration of these sources into the existing power grid is their erratic and sometimes discontinuous availability (volatility). Wind energy is one of the most relevant sources of CO_2 neutral electric energy, but volatile due to fluctuating wind fields on multiple scales. This has already been realized so that senors provide real-time information on the scale of individual wind turbines. However, forecasting remains an unresolved problem since numerical weather prediction models cannot provide the necessary level of detail. New modeling strategies are required that integrate turbine-scale and meso-scale information for accurate site-specific short-term prediction. Present and forthcoming research aims to incorporate fluctuations on multiple levels of fidelity, depending on the abstraction layer.

Main objectives

- Real-time forecast of fluctuating wind fields and power availability down to the turbine scale
- Cost-efficient modeling based on reduced order approaches
- Development of a hierarchical modeling framework encompassing several layers of abstraction

Expertise and background

The **Chair of Numerical Fluid and Gas Dynamics (NSG)** has accumulated solid experience in forward modeling and simulation of turbulent flows, including atmospheric flows. Young researchers are integrated into the research activities at an early stage, opening up the possibility for fast transfer of state-of-the-art academic research into applications. Research activities are bundled in the newly established **Young Investigator Group (YIG)** of the Scientific Computing Lab (SCL) of the Energy Innovation Center (EIZ) as sketched in **Fig. 1**. The YIG is hosted by the NSG.

Figure 1: Overview of the Energy Innovation Center (EIZ).

The NSG offers courses in machine learning (ML) and stochastic approaches, among courses in Computational Fluid Mechanics (CFD) as summarized in **Fig. 2**. The module *Stochastic Methods for Flow Simulations* introduces novel stochastic turbulence and mixing models, such as ODT [1] and HiPS [2]. The module *Flow Modeling with Machine Learning* introduces a palette of methods relevant for application in fluid flows based on [3]. This expertise will put students in the position to join present research activities.

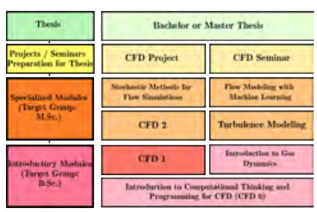

Figure 2: Overview of the courses offered by the Chair of Numerical Fluid and Gas Dynamics.

Data analysis and data-based modeling

Data-based abstraction is a straightforward way to construct very efficient models for site-specific wind fluctuations. Turbine-scale wind data is usually not accessible since it is owned by the operator of the wind turbine or the local power grid. Making this data publicly available constitutes a vulnerability to the critical infrastructure. In order to demonstrate the potential nevertheless, some measured, historic, and publicly available velocity time series [4] are used below. The simplest level of analysis is a Supervised Learning (SL) approach utilizing regression as shown in **Fig. 3(a)**. Wind measurements at different locations (e.g. in wind park) can then be correlated in order to reduce data and potentially yield a reduced order model for grid operation. This is exemplified in **Fig. 3(b)** by a Principal Component Analysis (PCA) for the wind velocity measured at three different locations.

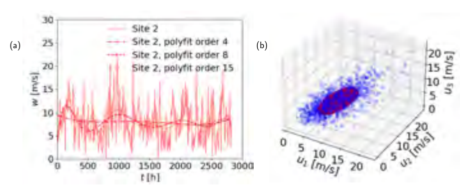

Figure 3: (a) Measured time series of the wind velocity $w(t)$ together with a polynomial regression analysis. (b) PCA of the fluctuating wind velocity $u_i(t)$ at three different locations $i = 1, 2, 3$.

Stochastic forward modeling with ML-based abstraction

The stochastic approach for evolving and vertical profiles of the momentary wind velocity is based on the One-Dimensional Turbulence (ODT) model [1]. The model reduction rationale aims to represent the effects of 3-D turbulence along a 1-D domain (vertical line of sight pointing in z direction) by spatial mappings that punctuate continuous deterministic (diffusive) advancement [5, 6, 7, 8]. Despite the reduced dimensional order of the model, mutltiple length scales in the atmospheric flow produce large amounts of data. The parametric space associated with overturning turbulent motions (eddies) enables accurate modeling of small scale dynamics in the atmospheric boundary layer and, hence, on the scale of wind turbines. **Fig. 4** shows the evolution of a simplified polar daytime ($Fr = 1000$) and polar nighttime ($Fr = 10$) atmospheric boundary layer in terms of different flow variables and discrete eddy events (blue bars in bottom panel) [6].

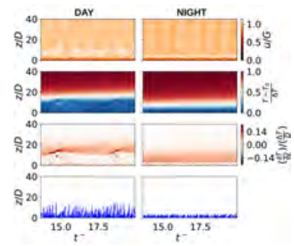

Figure 4: Space-time diagram of two stochastic ODT simulations of an idealized polar daytime ($Fr = 1000$, weakly stable) and polar nighttime (very stable, Fr = 10) atmospheric boundary layer.

Last, **Fig. 5** shows pairwise clusterings of model surrogate data in terms of ODT eddy event properties. The aim is to analyze the current flow state at a given wind turbine site in terms of turbulent scales, locations, and available eddy energy. This is the first step towards a further reduced model of local wind field for incorporation into network models of the power grid. The analysis is physically interpretable, providing means for detailed analysis of the site-specific flow state and, hence, more accurate short term predictions.

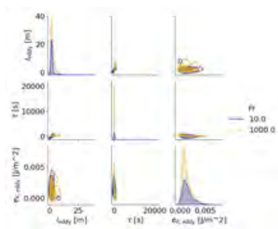

Figure 5: Clustering by pairwise statistics of ODT eddy events for the cases in **Fig. 4**. Note that the plots along the diagonal in the figure show the form of the univariate marginal distribution of the (repeated) axis variable.

Conclusions

- Volatility is a crucial aspect of next generation energy systems, in particular, for incorporation of wind energy.
- Multiscale modeling strategies with predictive capabilities are needed in order to proceed towards real-time analysis on the grid level, while incorporating turbine-scale information.
- The combination of stochastic and ML-based reduced order modeling approaches addresses predictability and efficiency aspects.

Forthcoming research

- Coupling of stochastic modeling and conventional numerical weather prediction (NWP) models
- Development of application-oriented abstraction layers with different levels of fidelity and abstraction

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References

[1] A. R. Kerstein, *J. Fluid Mech.* **392**, 277 (1999).
[2] A. R. Kerstein, *J. Stat. Phys.* **153**, 142–161 (2013).
[3] S. L. Brunton, J. N. Kutz, *Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control* (Cambridge University Press, 2019).
[4] Wind_speed, Wind speed measurements on three different sites; database from The Data and Story Library, https://dasl.datadescription.com/datafile/wind-speed/?_sf_s=wind&_sfm_cases=4+59943. Accessed: 2022-06-16.
[5] A. R. Kerstein, S. Wunsch, *Boundary-Layer Meteorol.* **118**, 325 (2006).
[6] M. Klein, H. Schmidt, *Adv. Sci. Res.* **19**, 117 (2022).
[7] Rakhi, M. Klein, J. A. Medina Méndez, H. Schmidt, *J. Turbul.* **20**, 506 (2019).
[8] M. M. Fragner, H. Schmidt, *J. Turbul.* **18**, 899 (2017).

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Einordnung in: KI-Lehre, KI-Transfer

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