

2D to 3D Wind Speed Data Reconstruction for Development of Low-Cost Monitoring Systems

Doyup Kwon¹, Pierce Rubenstein², Jaeyoung Jung³, and Marco G. Giometto⁴

¹Civil and Environmental Engineering and Earth Studies, University of Notre Dame, Notre Dame, IN

²Mechanical Engineering Department, The College of New Jersey, Ewing, NJ

³Department of Civil Engineering and Engineering Mechanics, Columbia University, New York, NY

Introduction: To generate reliable simulations of boundary layer flows on the regional scale, large-scale monitoring systems collecting spatiotemporal in-situ measurements are essential. Using 2D anemometers instead of 3D sensors significantly reduces costs and allows a denser monitoring network with additional stations. To make this substitution possible, it is necessary to reconstruct the vertical component of the wind velocity, w , from the measured horizontal velocity vector (u , v). The present study aimed to develop a machine-learning-based reconstruction of vertical wind velocity w to facilitate the reliability of 2D anemometers in the field.

Methods: To collect the data required for statistical analysis, a ten-foot surveying tower was deployed within the boundary layer on the roof of the Mudd Building. Wind speed data was measured with a 3D anemometer at 20 Hz and a 2D anemometer at 1 Hz for 10 days. Longwave and shortwave solar radiation, a vertical temperature gradient, and a vertical humidity gradient were also measured at 1 Hz for 10 days. Post-processing was then performed with fast Fourier transforms to derive power density spectrums for each dataset.

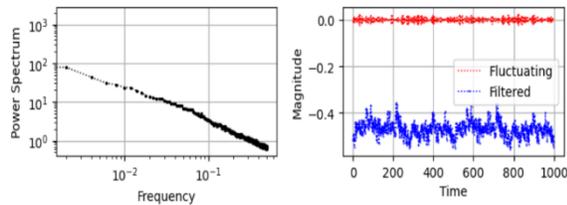


Figure 1. Power Spectrum Density Plot with Corresponding Timeseries

The data was then examined for statistical relationships based on meteorological principles¹, such as velocity component fluctuations, Reynolds shear stress values, turbulent kinetic energy, temperature and humidity gradients and buoyancy, and correlations between means and standard deviations. Further analysis was performed by observing trends within the timeseries data and performing fractal dimensional analysis.²

Results: It was found that preprocessing through removing outliers, detrending, and decomposition of the timeseries data before prediction of the fluctuating vertical velocity component lead to decent prediction of trends. It was also found that a combination of horizontal speed, temperature, and humidity data best informed the predictive models.

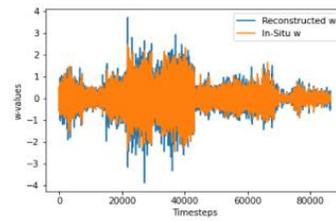


Figure 2. Reconstructed vs. In-Situ Vertical Velocity Timeseries

Conclusions: This study serves as a proof of concept for the possibility of reconstruction of vertical velocity through the use of related measurements and data-driven predictive models. Although perfect reconstruction was not achieved, several relationships and dependencies were observed, including varying correlations between vertical velocity and fluctuating components of timeseries data for different variables, that can be utilized in order to improve model performance.

Future Study: Two additional methods identified for increasing accuracy of reconstructed data are the use of more advanced machine learning models and the inclusion of a sensor's specific topography in the reconstruction phase. Our lab plans to deploy a network of 8 towers with 2D and 3D anemometers to continue this work with more varied data.

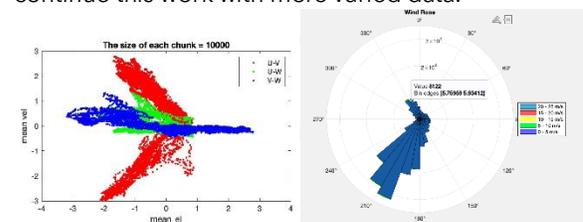


Figure 3: Example Spatial Dependencies. Left: Horizontal Wind Interactions due to Obstruction. Right: Wind Rose Showing Dominant Wind Directions

References:

- [1] Stull, R. B. (1988). *An introduction to boundary layer meteorology* (Vol. 13). Springer Science & Business Media.
- [2] Shu, Z. R., Chan, P. W., Li, Q. S., He, Y. C., Yan, B. W., Li, L., ... & Yang, H. L. (2021). Characterization of vertical wind velocity variability based on fractal dimension analysis. *Journal of Wind Engineering and Industrial Aerodynamics*, 213, 104608.

Acknowledgements: This material is based upon work supported by, or in part by, the Army Research Laboratory and the Army Research Office under grant number W911NF-22-1-0178. We would like to thank Carleton Laboratory and its staff, especially Freddie Wheeler Jr., for their help and support with our equipment. We would also like to thank Ken Conner at Campbell Scientific for training us and offering guidance regarding the tower setup process.