Capstone Proposal (Draft Zero): Offshore Wind Turbine Power Prediction and Wind Capacity Analysis Using LIDAR

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1 Introduction

At the end of 2019, the total installed wind power capacity in the United States was 105,583 Megawatts (MW) and the potential wind power capacity of the United States (at an 80 meter (m) turbine hub height) and its territories exceeded 10,640,000 MW. [5] This makes wind the largest source of renewable energy in the country. [1] Successful integration of wind power resources into the national energy infrastructure, though, poses a number of challenges induced by the variability of wind energy availability including ramp events (rapid changes in demand or surplus of electrical production), induced wear and expanded emissions as a result of cycling traditional power production facilities up and down in their output, and increased management difficulty in balancing traditionally variable demand with a more stochastic input. [2] The ability to forecast wind values (speed and direction) is a key component of any solution to help energy operators successfully manage and integrate wind power into the existing energy grid.

2 Proposal

In this research, we seek to explore statistical time series, machine learning, and appropriate ensemble approaches to enable the forecasting of wind strength, and as a result theoretical power generation, at given wind turbine hub heights and rotor diameters with a forecasting horizon of 10 minutes up to 24 hours. These prediction windows are selected to allow models to support load balancing and reserve power management in the immediate near term (10 minutes to one hour) and "day-ahead" energy demand markets that support day-to-day grid planning. [3]

3 Wind Modeling

In his book, "Data Science for Wind Energy", Prof. Ding identifies two primary approaches to wind forecasting. The first, Numerical Weather Prediction

(NWP), is built on modeling of atmospheric data to produce outputs similar to the weather forecast used to predict daily weather and/or hurricane events. This model generally performs well on longer time scales, but requires intense computing power to execute. [3] A second approach uses smaller scale, local sensor data to make statistical predictions based on single time series, sample-based modeling. [3]

Our approach will be to first explore the techniques and modeling methods associated with the creation of time series based forecasting of wind at a specific site given historical wind values on specified intervals and with co-located sensor data of interest. If successful, we then hope to expand and improve our time series based forecast by incorporating features derived from data collected more traditionally in support of NWP modeling (such as regional temperature, wind speed, wind direction, barometric pressure, and similar values) and/or the development of ensemble machine learning approaches that can contribute to or compete with the time series prediction.

4 Wind Buoy Program

The U.S. Department of Energy (DOE) Office of Energy Efficiency and Renewable Energy (EERE) with the support of Pacific Northwest National Lab (PNNL) is currently supporting the deployment of an offshore wind energy evaluation effort using 20,000-pound buoys known as WindSentinel to measure meteorological and oceanographic parameters related to wind energy capacity. These buoys make use of Light Detection and Ranging (LIDAR) and other instruments to measure wind speed and direction, air and sea temperature, local barometric pressure, relative humidity, wave height and period, water conductivity, sub-surface currents, and other values in one second intervals. [4]

Both historical and current buoy data from multiple locations are available to support model training and evaluation. Historical data includes data collected from between 2014 and 2017 in offshore locations near both Virginia and New Jersey. Active collection is ongoing off the coast of Massachusetts providing the opportunity to evaluate the model against real-world new data that is regularly being updated.

Additional data sources of interest include similarly collected 10-minute interval LIDAR data made available by the Danish firm Orsted from three unique offshore wind farm and meteorological station locations. [6] Also, the Ding, 2019 text contains a number of data sets provided as exemplars of the methodologies described in the text from both on and off-shore locations that may be of additional interest, but which require exploration. [3]

NWP weather data is available publicly from a number of sources including the U.S. National Weather Service. Availability of data of interest to our specific area of research is still being explored by the research team.

5 Sensors

5.1 LIDAR Background

Need to insert tutorial information regarding how LIDAR is used to measure wind speed at various altitudes. Discuss the doppler detection of aerosols.

5.2 Vindicator and WindCube Sensors

The first version of WindSentinel deployed during 2014-2017 used a Vindicator III LIDAR sensor to measure wind speeds at a variety of heights. The more recent ongoing survey in Massachusetts uses a WindCube sensor. Both sensors face challenges with noise induced by environmental concerns, the foremost being that the sensor is mounted on a gimble on a floating platform and is still subject to some pitch, roll, and yaw adjustments that impact the variance of its measurements.

Multiple approaches to address this are used by PNNL and DOE including a smoothing function applied to the 1 second interval data (1Hz data) or the chunking of data into 10 minute averages.

Work is ongoing within the group to explore the data, fields available, and the appropriate altitude that will allow the minimum amount of information lost and be most representative of the wind turbine use case. Further, we have completed functions to import data of both Vindicator III and WindCube output formats into our analytic environment.

6 Advisors

In order to gain assistance in guiding this research, the team has reached out to a number of both Southern Methodist University faculty members and academic / professional researchers in the field of wind energy. To date we have secured the following interest:

- Dr. Y. Ding, Texas A&M University: Although Dr. Ding is likely unable to act as our formal advisor, he has expressed willingness to respond to our specific questions related to the methodologies outlined in his book and to help steer our analysis when needed.
- Dr. B. Sadler, Southern Methodist University: Dr. Sadler has expressed willingness to help guide the time series aspects of our analysis, but is unable to act as our advisor due to other commitments.
- Dr. A. Gorton, Pacific Northwest National Labs: Dr. Gorton is one of the lead researchers of the DOE BUOY LIDAR project. She is considering specific research questions that may be of interest to the effort and ways in which we might contribute.
- Mr. B. Blanchard, Southern Methodist University: We have sought out Mr. Blanchard for his expertise in applied machine learning technologies and are awaiting a response.

References

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