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Leveraging Data-Driven Techniques in LiDAR and SCADA Data to Enhance Analysis of Floating Offshore Windfarm

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Introduction

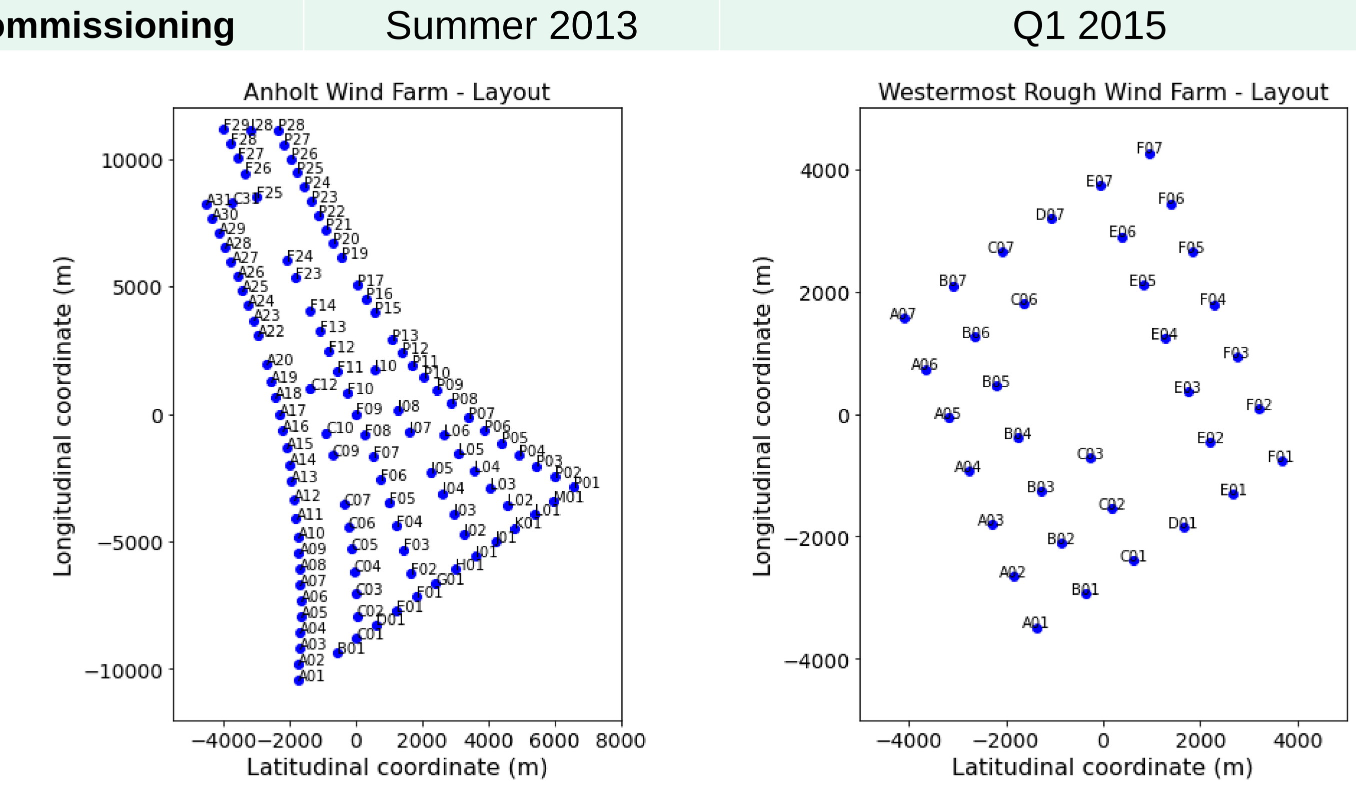
SCADA provides turbine performance metrics, while LiDAR captures wind profiles, offering valuable insights for optimizing offshore wind farm efficiency. Data-driven methods enable advanced insights into wind farm data by improving input data quality, efficient data extraction and uncovering critical patterns and relationships within the data. This study applies XGBoost and Bi-LSTM techniques to analyze data from Anholt and Westermost Rough offshore wind farms.

Wind farms and Dataset

Comparative table of key parameters for the Anholt and Westermost Rough (WMR) Offshore Wind Farms:

Parameter	Anholt	Westermost Rough
Location	Kattegat, Denmark	North Sea, UK, 8 km off Yorkshire coast
Number of Turbines	111	35
Turbine Capacity (MW)	3.6	6
Total Capacity (MW)	400	210
Rotor Diameter (m)	120	154
Hub Height (m)	81.6	102
Wind turbine foundation	Monopile	Monopile
Water Depth (m)	15-19	16 – 20
Distance to Shore (km)	15	10
Commissioning	Summer 2013	Q1 2015

Wind Farm Layout



The **dataset** for the wind farms include LiDAR and SCADA data, offering detailed insights into wind and turbine performance. LiDAR data captures wind speed, direction, and environmental conditions at multiple heights, with corrections applied based on the site. SCADA data provides operational parameters like turbine ID, wind speed, yaw position, blade pitch, and power output, recorded in 10-minute intervals.

Concluding remarks

- The work is ongoing, with initial results demonstrating the effectiveness of data-driven methods like XGBoost and Bi-LSTM for prediction.
- XGBoost achieved an R^2 of 0.969, an MSE of 0.003, and an RMSE of 0.064, while Bi-LSTM effectively captures offshore wind variability.
- Both methods were effective in predicting wind speed and providing time-series forecasting capabilities.

Acknowledgement

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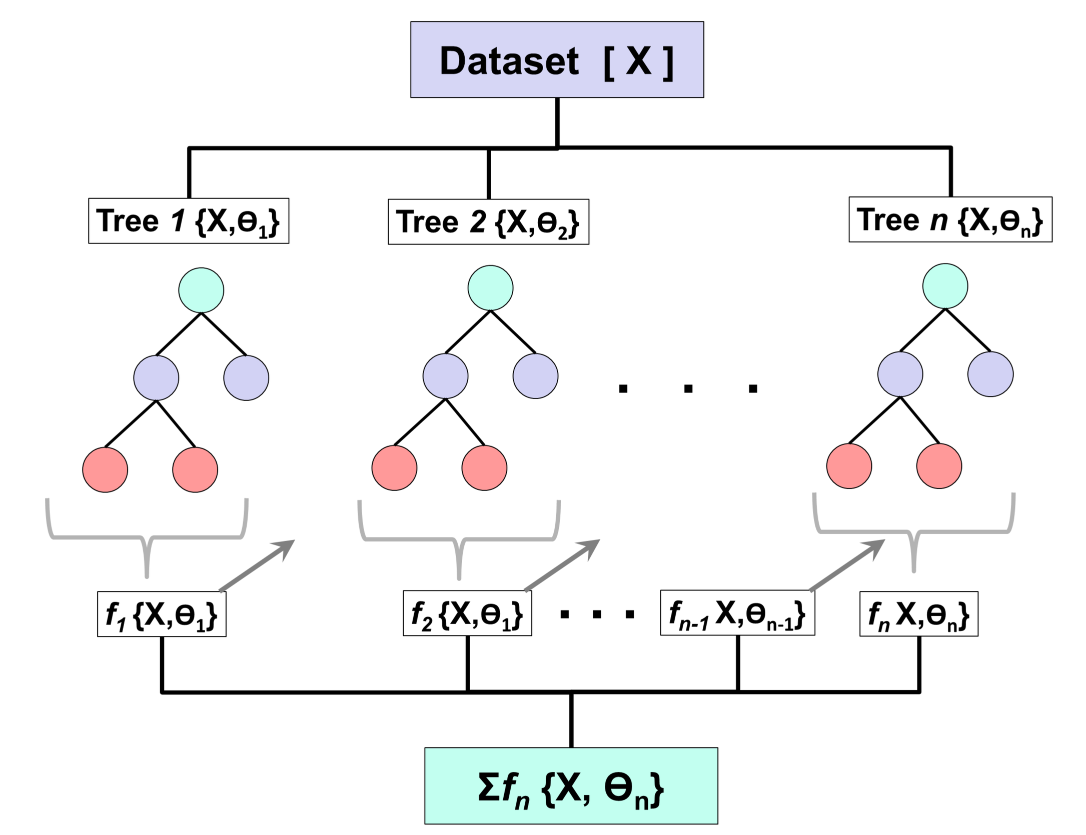
Methods

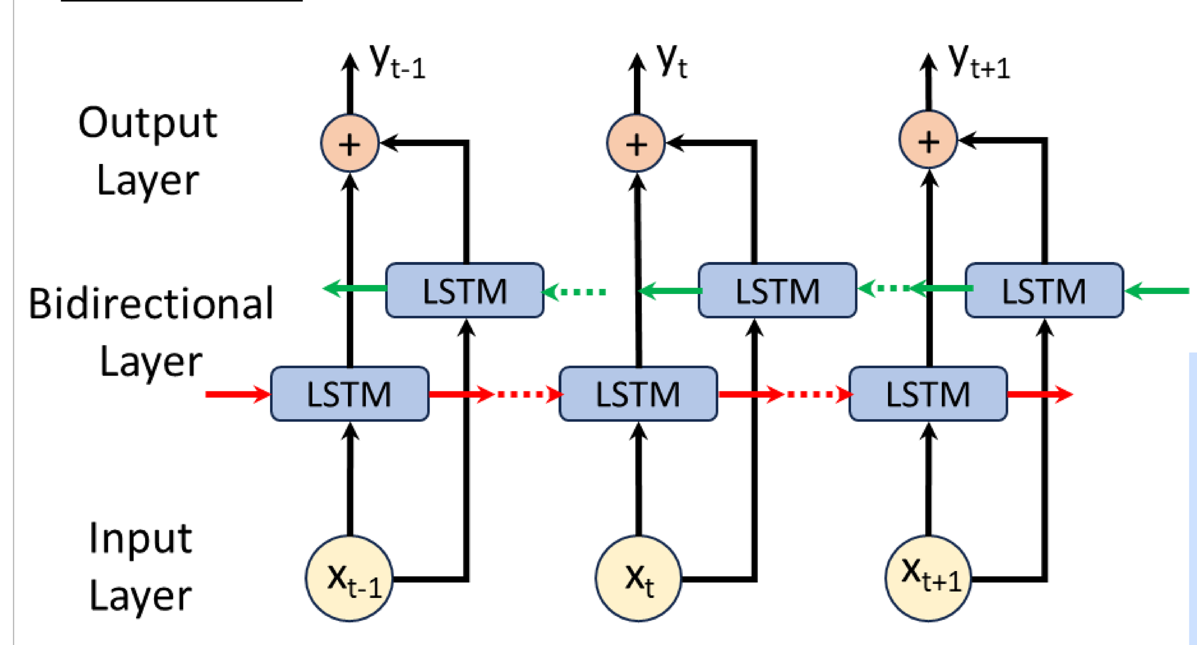
XGBoost



1. Data preparation
2. Feature engineering
3. Boosting iterations
4. Training and optimization
5. Prediction

XGBoost excels with gradient boosting and L1/L2 regularization to prevent overfitting and improve generalization. Its tree pruning, parallel computation, and feature importance ranking make it scalable and fast for large datasets.

Bi-LSTM

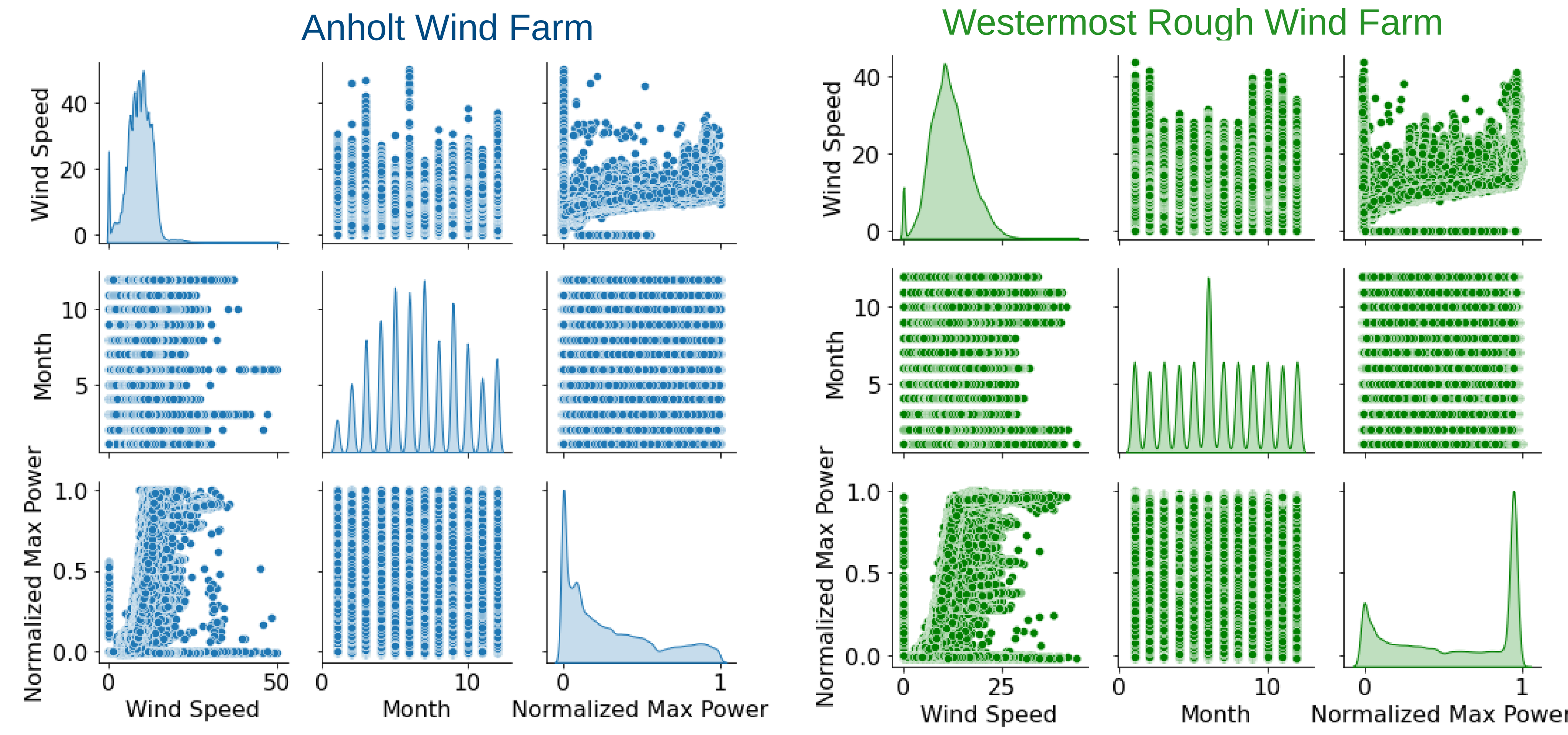


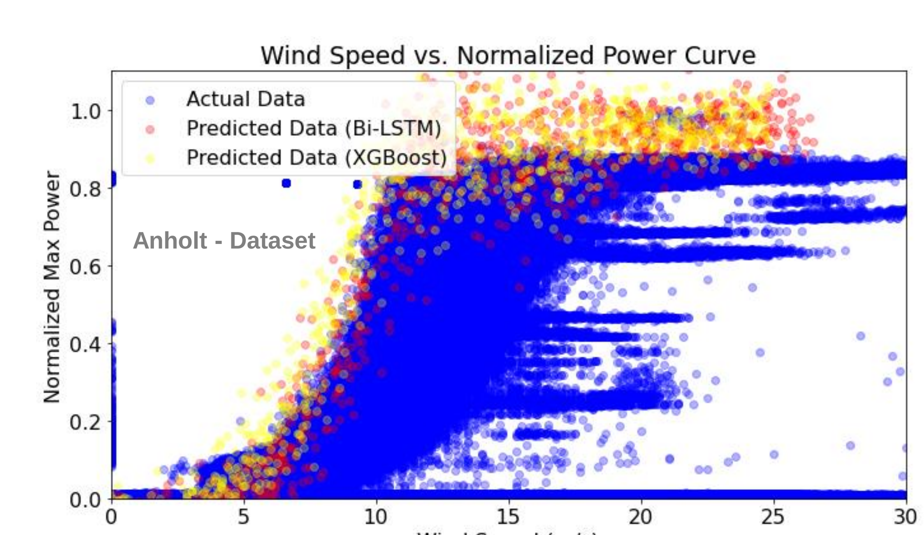
1. Data preprocessing
2. Bi-LSTM architecture
3. Training and optimization
4. Prediction

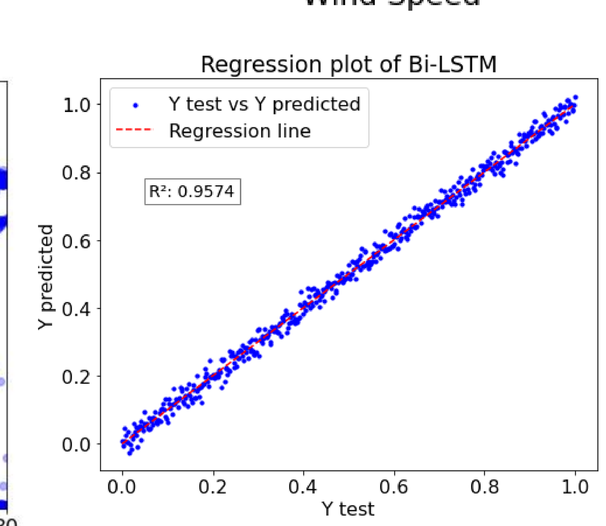
Bi-LSTM captures past and future context for better predictions, with gating mechanisms (input, forget, output) that handle long-term dependencies and prevent vanishing gradients.

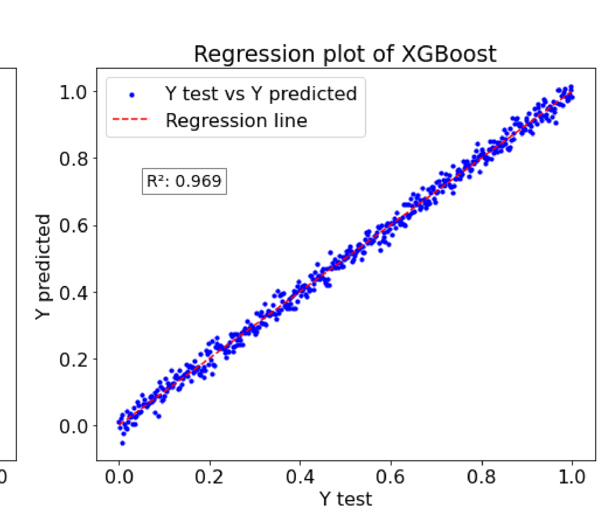
Results

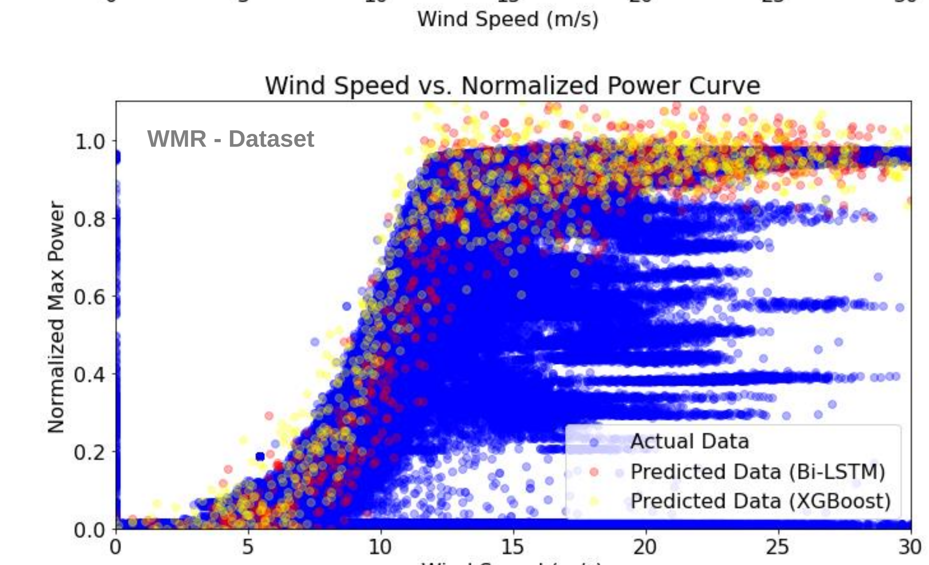
Pair plot of selected variables

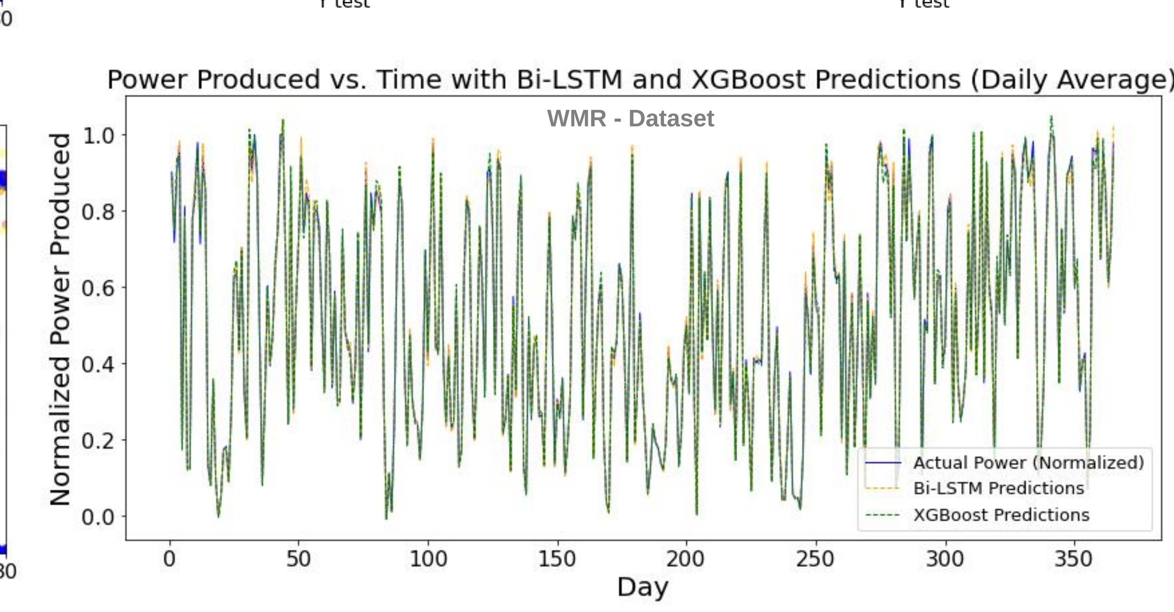












Collaborators

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