Weathering the Sky: GNNs for UAV Micro Forecasts

Gavin S. Halford, Benjamin M. Hand

Electrical Engineering, University of North Texas

Abstract

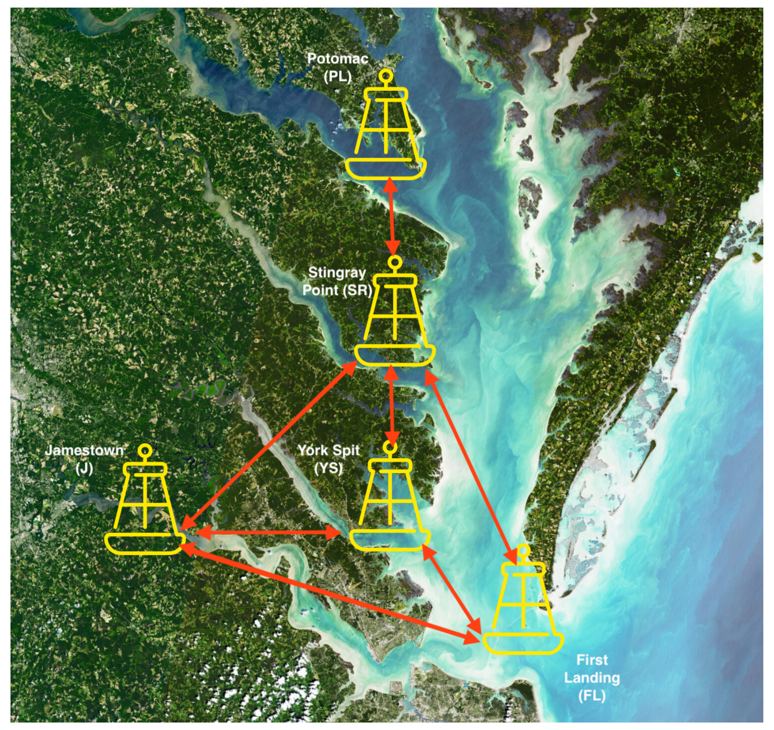
Unmanned Aerial Vehicles (UAVs) have the potential to transform the future. However, UAV operations are subject to strict restrictions due to safety concerns, particularly regarding wind conditions. This research explores the use of Graph Neural Networks (GNNs) for micro-weather forecasting in UAV air corridors. We utilize NOAA buoy data from Chesapeake Bay to create a predictive model. By modeling the air corridor as a graph, we improve wind predictions by capturing spatial and temporal patterns from weather sensors. Although the model shows promise in forecasting, challenges still remain. This work aims to enhance real-time weather awareness and operational planning for UAVs operating in controlled airspace.

Problem Definition

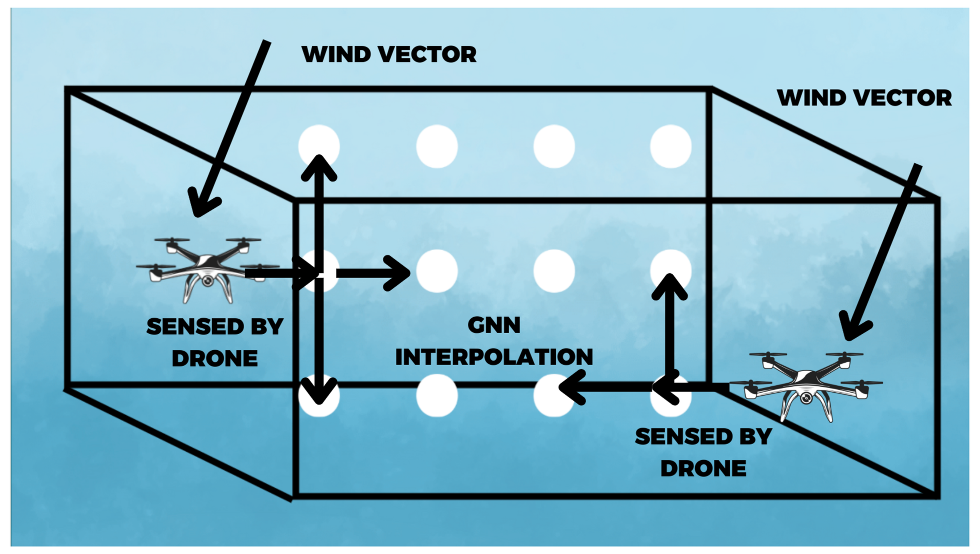
- Current forecasting methods are not granular enough for UAV operations.
- Small-scale atmospheric changes affect UAV flight safety.
- Accurate micro-weather forecasting is essential for FAA airspace integration.

Data

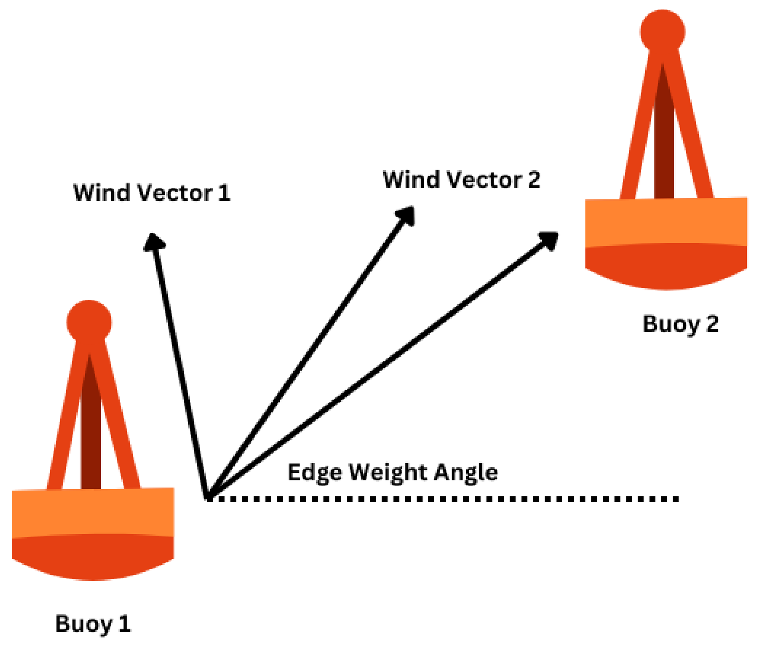
- NOAA buoy data from Chesapeake Bay used to train the model.
- Three years worth of data used.
- Distance between Bouys range from 30 - 120m,



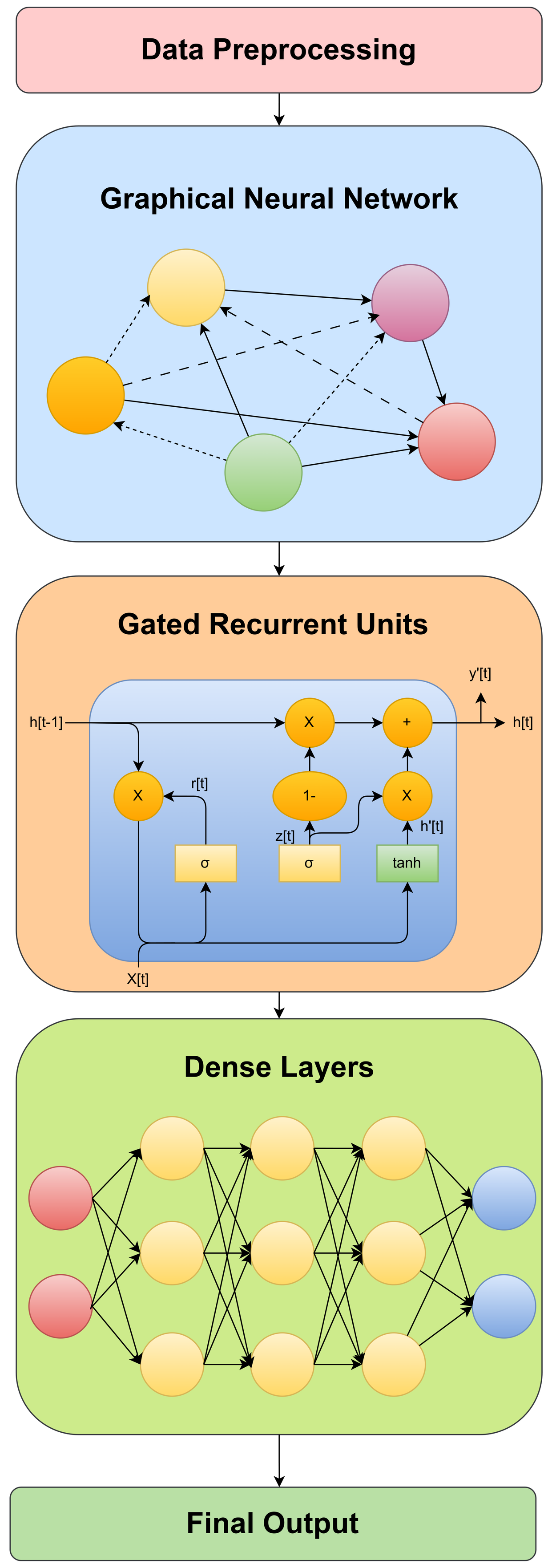
Problem Solution



- Air Corridors are Highways in the sky, guiding UAV traffic safely.
- UAVs map wind data to the nearest node in an air corridor.
- The GNN interpolates missing weather data between nodes.
- More UAVs improve data resolution and forecasting accuracy.
- GNNs dynamically model spatial dependencies better than CNNs.



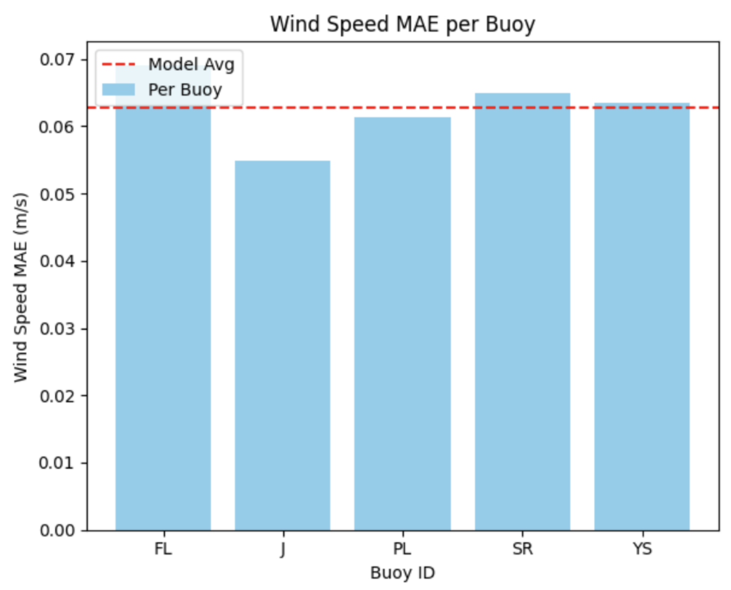
Architecture

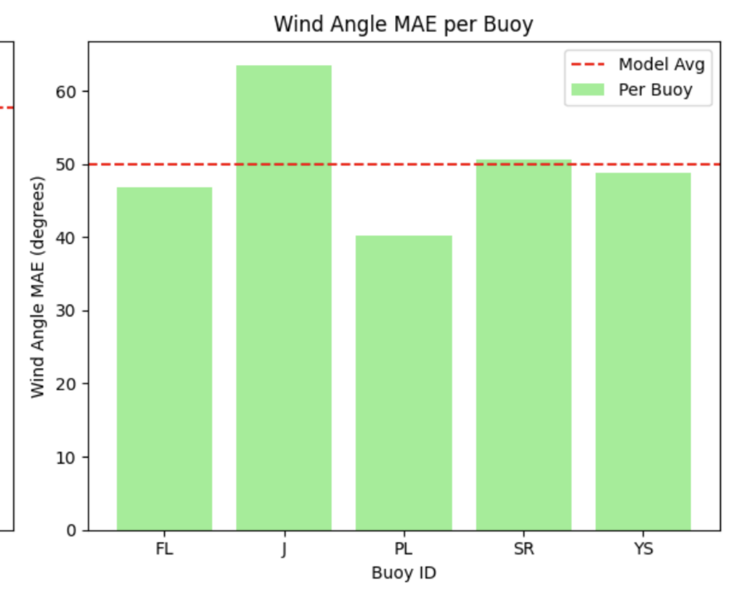


- ECCConv layers capture spatial dependencies, while GRUs model temporal weather patterns.
- Hybrid loss improves accuracy, batch normalization and LeakyReLU ensures stable training.

Results

- The model effectively predicts wind speed, with an average error of 0.06 m/s.
- Directional prediction remains challenging, with an average angular error of 49.87°.
- The Edge-Conditioned Convolution GNN model outperforms other approaches.





Comparison

Table: Predicted vs. Actual Wind Speeds and Directions

Pred Speed	Pred Direction	Actual Speed	Actual Direction
0.6260	83.09	0.6143	84.46
0.6267	82.17	0.6495	80.07
0.6311	81.17	0.6394	81.44
0.6289	83.09	0.6380	80.13
0.6323	81.64	0.6526	80.82
0.6240	83.12	0.6428	79.40
0.6218	82.73	0.6310	82.12
0.6340	81.52	0.6533	81.45
0.6266	83.56	0.6231	83.27
0.6351	81.58	0.6188	82.77

Conclusion

This study validates the potential of GNN-based models for micro-weather forecasting in UAV operations, achieving accurate wind speed predictions while highlighting the complexity of wind direction estimation. The Edge-Conditioned Convolution (ECCConv) approach proved most effective in capturing spatial dependencies, outperforming traditional methods such as persistence and nearest-neighbor models. Future work will focus on refining angular prediction accuracy, expanding the graph structure to 3D representations, and integrating real-time UAV sensor data. By improving high-resolution weather forecasting, this research supports safer and more efficient UAV navigation, marking a step toward dynamic, real-time atmospheric modeling in airspace management.

References

[1] National Oceanic and Atmospheric Administration (NOAA), "Noaa chesapeake bay buoy data collection," 2024, accessed: 2024-02-14. [Online]. Available: https://buoybay.noaa.gov/

[2] World Meteorological Organization, *Guide to Instruments and Methods of Observation*, 2023rd ed., ser. WMO-No. 8. Geneva, Switzerland: World Meteorological Organization, 2023.

[3] F. Scarselli, M. Gori, A. C. Tsoi, M. Hagenbuchner, and G. Monfardini, "The graph neural network model," *IEEE Transactions on Neural Networks*, vol. 20, no. 1, pp. 61–80, 2009.

[4] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in python," pp. 2825–2830, 2011. [Online]. Available: https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.RobustScaler.html

[5] Federal Aviation Administration, "Title 14 CFR Part 107 - Small Unmanned Aircraft Systems," 2025, accessed: 2025-02-13. [Online]. Available: https://www.ecfr.gov/current/title-14/chapter-I/subchapter-F/part-107