The 2024 World Congress on
The 2024 Structures Congress (Structures24)
19-22, August, 2024, The K hotel, Seoul, Korea

Enhancing Meteorological Forecasting in Extreme Climate Conditions with Spatio-temporal Graph Neural Networks and Transformer Deep Learning Technology

*Jia-Hao Lu[1)], Zheng-Wei Chen [2)] and Yi-Qing Ni [3)]

[1), 2),3)] Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong, People's Republic of China
[1), 2),3)] National Rail Transit Electrification and Automation Engineering Technology Research Center (Hong Kong Branch), Hong Kong, People's Republic of China
[1)] jia-hao.lu@connect.polyu.hk

ABSTRACT

Accurately predicting meteorological attributes, such as wind speed, is crucial for addressing challenges posed by extreme weather events. The impact of these predictions extends beyond enhancing the efficiency of the energy industry to directly influence urban safety and disaster preparedness planning. With the frequency and intensity of extreme weather events on the rise due to climate change, the importance of reliable forecasting methods becomes increasingly evident. This study introduces an innovative approach that utilizes spatial-temporal graph neural networks (STGNN) and Transformer architectures to reconstruct and forecast wind speed data, ultimately providing reliable future wind speed data to facilitate proactive disaster preparedness. The core framework integrates a Graph Attention Network (GAT) for data reconstruction with Transformer models for predicting future time steps operating on graph sequence. By combining the strengths of GNN in capturing spatial dependencies and Transformer in sequence modeling, this method offers a powerful tool for wind speed prediction. Empirical tests confirm that even with limited observational data or temporary failures at measurement points, the framework can achieve high-level reconstruction of anomalous data points and high-precision future predictions for all points of interest, demonstrating its practical value. The use of GAT enables the recovery of precise wind speed estimates in the presence of missing values, thereby enhancing the reliability of baseline data. Furthermore, the integrated STGNN-Transformer framework in the prediction process effectively captures spatiotemporal variations, reducing errors and improving accuracy. Notably, the reconstructed data supports predictions comparable to original observations, particularly advantageous for regions with limited data availability, thus addressing

---
[1)] Research Student
[2)] Research Assistant Professor
[3)] Professor

issues arising from incomplete records.