Structural Surrogate Modelling of a Floating Offshore Wind Turbine with Physics-Guided Spatial-Temporal Graph Neural Network

Presentation · January 2025

DOI: 10.13140/RG.2.2.36657.70246

5 authors, including:

Kobe H.Y. Yung
University of Strathclyde

Qing Xiao
University of Strathclyde

Structural Surrogate Modelling of a Floating Offshore Wind Turbine with Physics-Guided Spatial-Temporal Graph Neural Network

Kobe Hoi-Yin Yung[1,2]

Qing Xiao[1], Xiuqing Xing[2], Atilla Incecik[1], Chang Wei Kang[2]

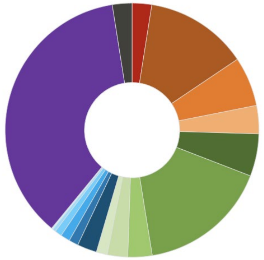
[1] University of Strathclyde Glasgow, UK

[2] Institute of High Performance Computing (IHPC) Agency for Science, Technology and Research (A*STAR) Singapore

Background & Motivation

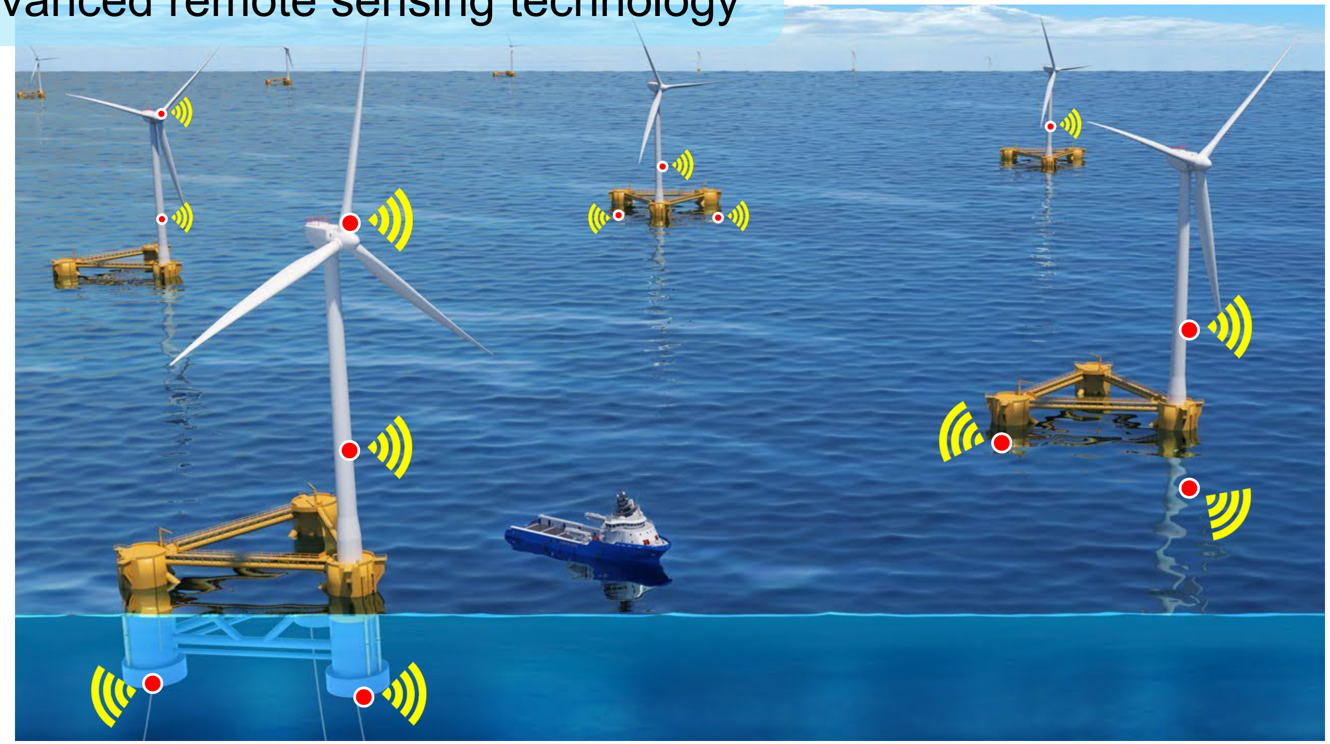
Structural Health Monitoring with advanced remote sensing technology

Lifetime cost of FOWT



- Development and project management **2.5%**
- Turbine rotor **6.3%**
- Cables **5.4%**
- Mooring systems **3.1%**
- Onshore substation **1.4%**
- Mooring and anchoring pre-installation **1.2%**
- Floating substructure - turbine installation **0.9%**
- Other installation **0.2%**
- Decommissioning **2.5%**
- Turbine nacelle **13.1%**
- Turbine tower **3.6%**
- Floating substructure **16.6%**
- Offshore substation **2.6%**
- Cable installation **2.5%**
- Floating substructure - turbine assembly **1.2%**
- Offshore substation installation **0.4%**
- Operations and maintenance **36.6%**

BVG Associates, "Guide to a Floating Offshore Wind Farm," 2023)



https://www.energy.gov/topics/floating-offshore-wind-shot

How to manage large scale floating wind farm (remotely)?

How to ensure structural integrity?

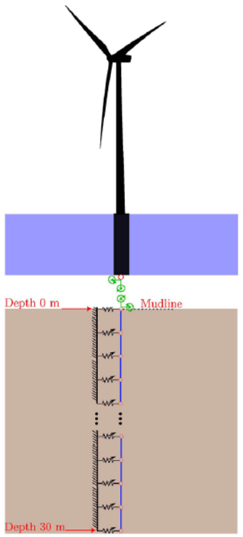
Digital Twin Technology!

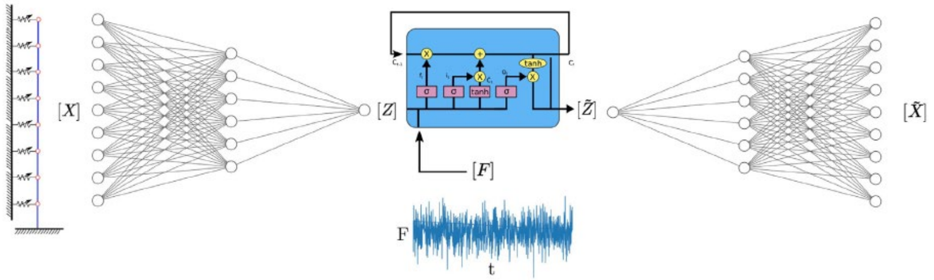
Background & Motivation

Existing Digital Twin Models and Reduced Order Methods

Academia

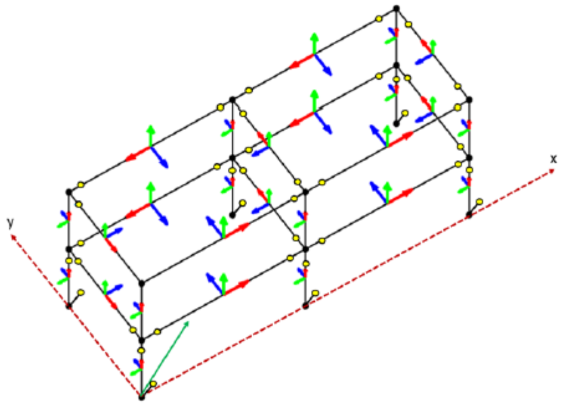
Deep Learning approach
e.g. Convolution Neural Network (CNN),
Long Short-Term Memory (LSTM),
Autoencoder (AE),
Variational Autoencoder (VAE)





T. Simpson, N. Dervilis, P. Couturier, N. Maljaars, E. Chatzi and E. Chatzi, "Reduced order modeling of non-linear monopile dynamics via an AE-LSTM scheme," Frontiers in Energy Research, vol. 11, 2023

T. Simpson, K. Vlachas, A. Garland, N. Dervilis and E. Chatzi, "VpROM: a novel variational autoencoder-boosted reduced order model for the treatment of parametric dependencies in nonlinear systems," Scientific Reports, vol. 14, no. 6091, 2024



Existing deep learning models only consider simple structures and a homogenous loading

Background & Motivation

Existing Digital Twin Models and Reduced Order Methods

Industry

e.g.

Limitation of commercial software:

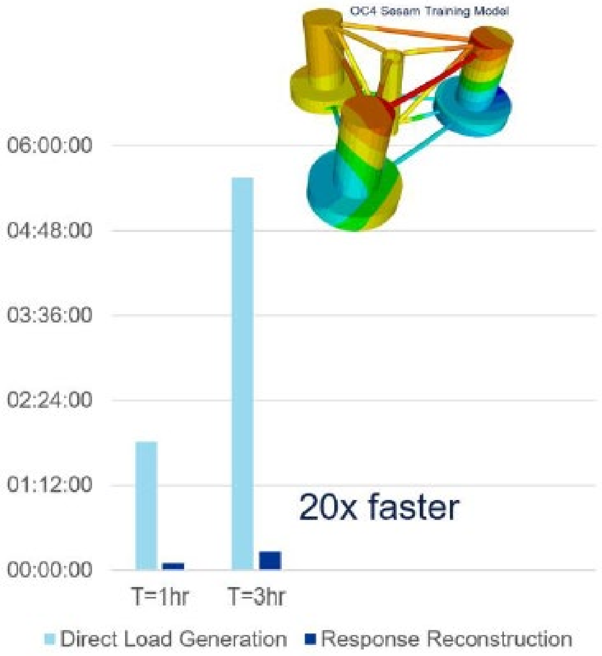
New method (DNV SESAM release notes July 2024)

5 DO YOU RECONSTRUCT 2ND ORDER INDUCED PRESSURES? SUCH AS WAVE DRIFT AND SUM FREQ? OR FOR EXAMPLE, IF YOUR COUPLED MODEL INCLUDES EFFECTS SUCH AS OTHER DAMPING, ARE THESE EFFECTS APPROXIMATED INTO THE PRESSURE FIELDS?

Answer: For your first question, the answer is No. For your second question, for those effects (e.g other damping), cannot be easily approximated as distributed pressure.

Semisubmersible type platform is prone to the second order hydrodynamic load

DNV, "New fast time domain simulation methods for floating wind substructure design webinar Questions and Answers," 2024. https://brandcentral.dnv.com/fr/gallery/10651/files/highres_pdf/151dadc6-da3b-489d-bc90-5b1d7e93b78a.pdf



DNV, Sesam for Floating Wind Time Domain Workflows, July 2024

How to improve?

A New Deep Learning Model for
Real-time Finite Element Structural Modelling

Physics-Guided Spatial-Temporal Graph Neural Network

Physics-Guided Spatial-Temporal Graph Neural Network

Wind speed 13.63 m/s

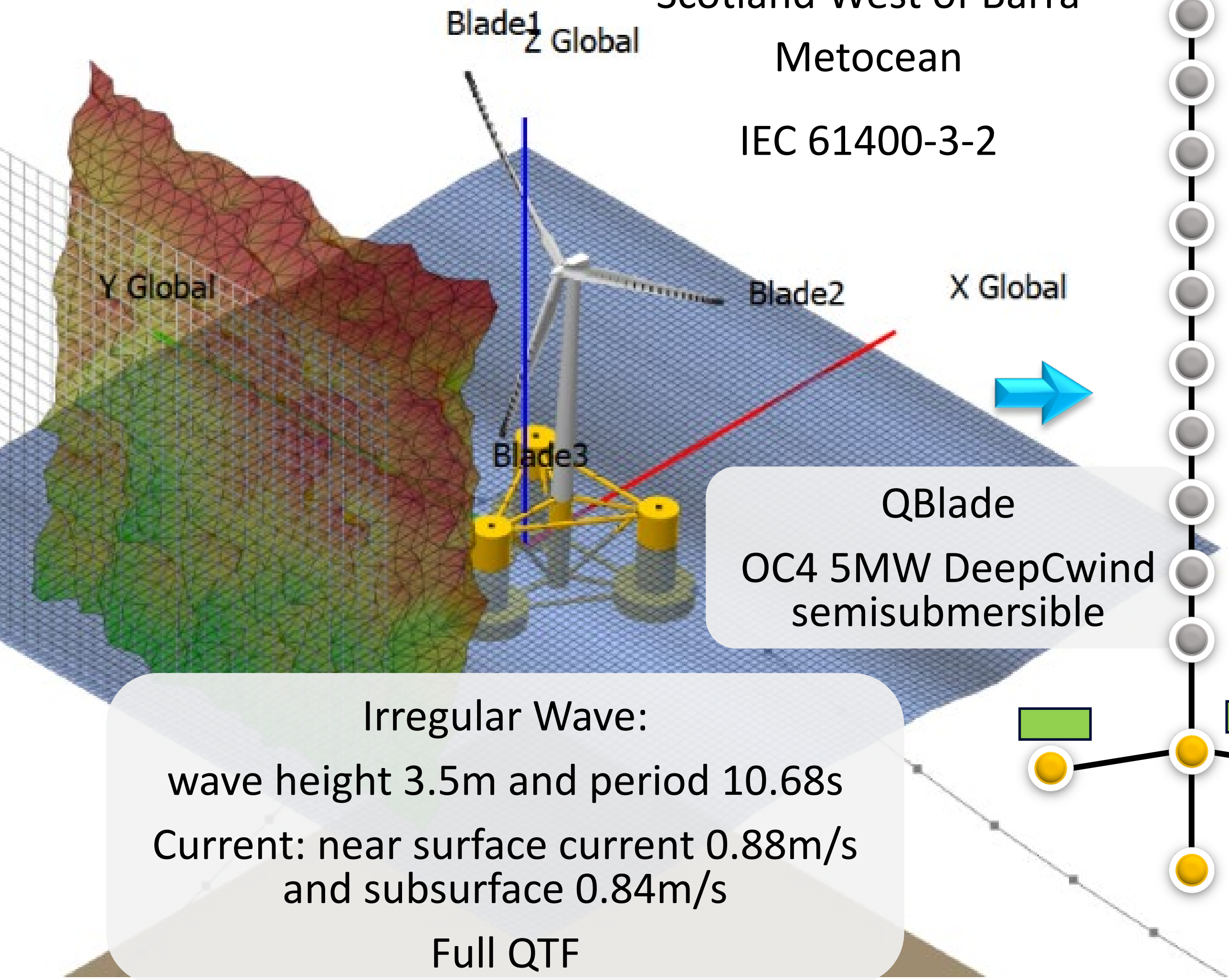
Turbulence Class IC Kaimal model

*LIFES50+ Project

Scotland West of Barra

Metocean

IEC 61400-3-2



QBlade

OC4 5MW DeepCwind semisubmersible

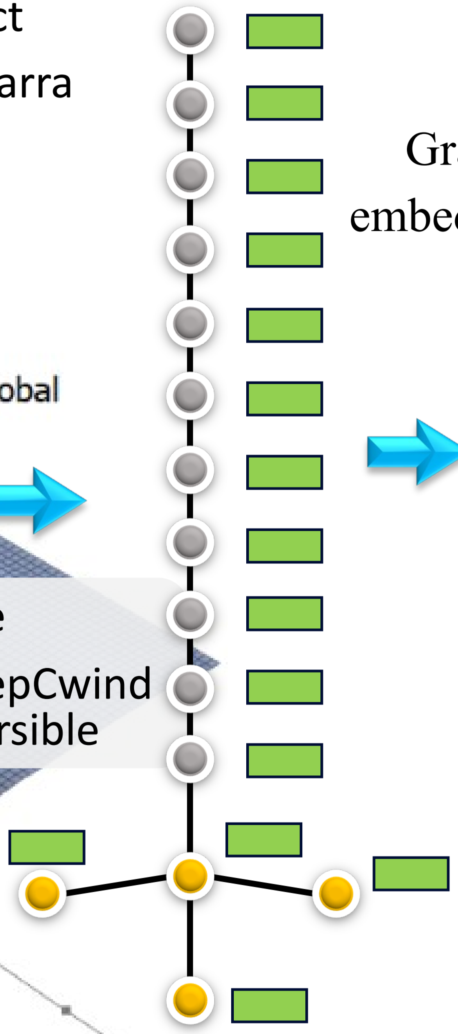
Irregular Wave:

wave height 3.5m and period 10.68s

Current: near surface current 0.88m/s and subsurface 0.84m/s

Full QTF

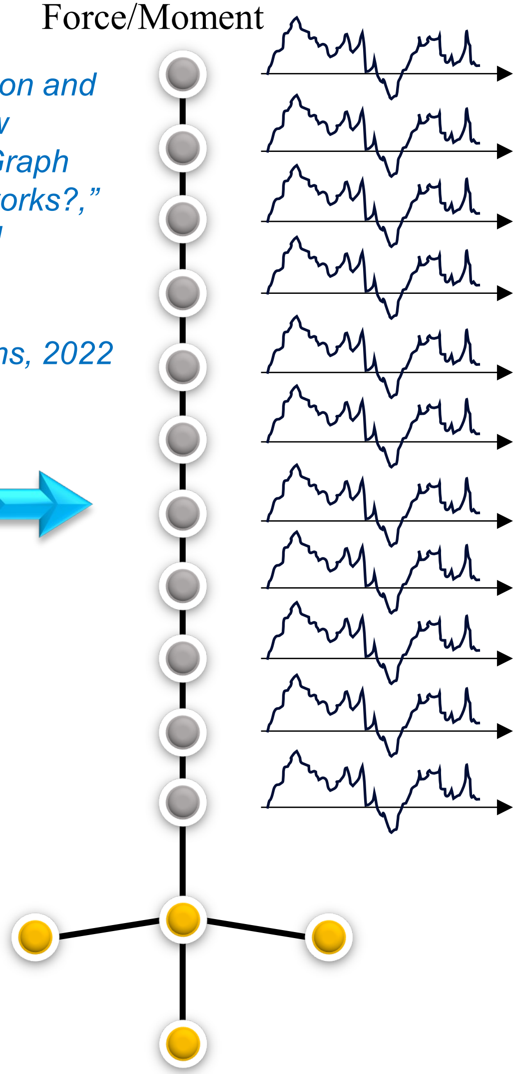
Graph Attention Network (GAT) or GATv2



Graph embeddings

S. Brody, U. Alon and E. Yahav, "How Attentive are Graph Attention Networks?," in International Conference on Learning Representations, 2022

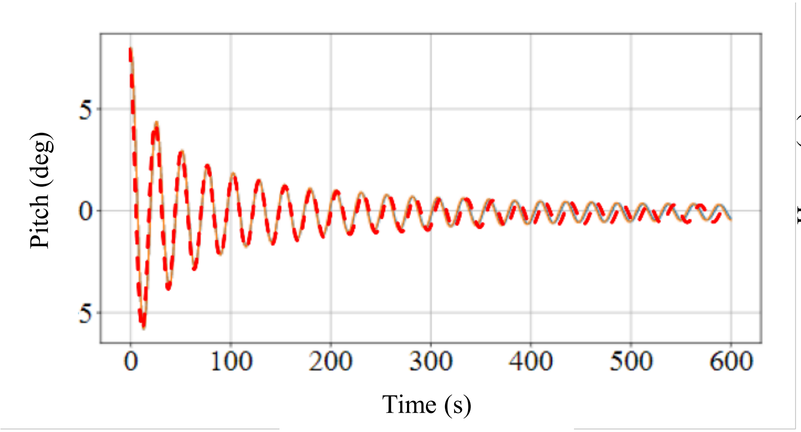
Temporal Dynamics (LSTM or GRU)

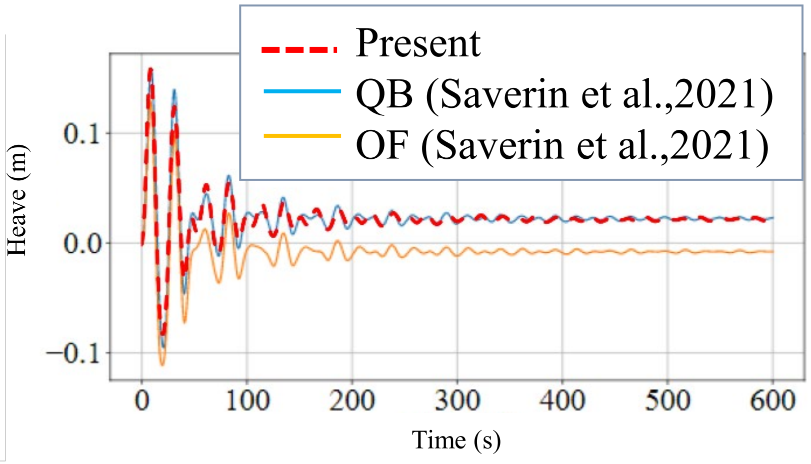


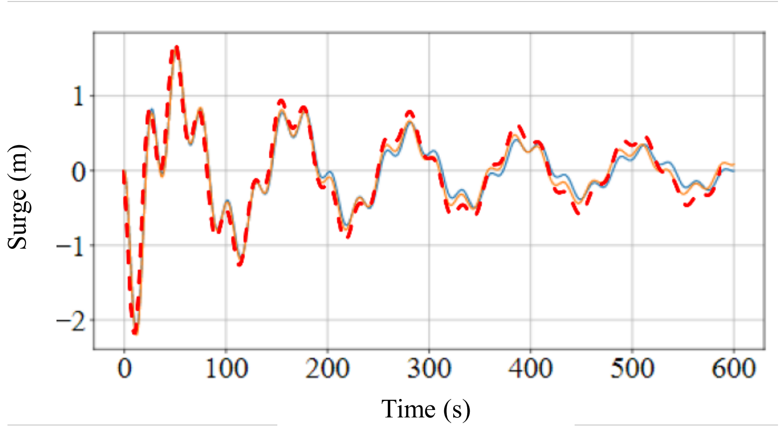
Real-time Dynamic Force Prediction

Physics-Guided Spatial-Temporal Graph Neural Network

Validation of present QBlade model for Physics-Guided Spatial-Temporal Graph Neural Network training

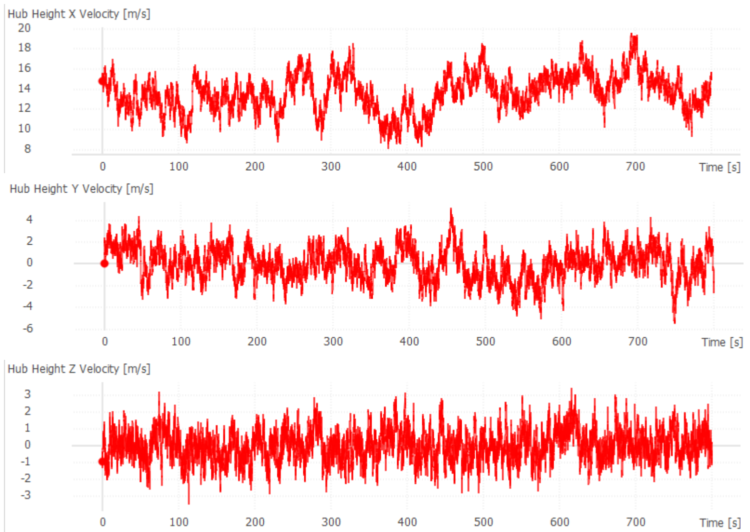




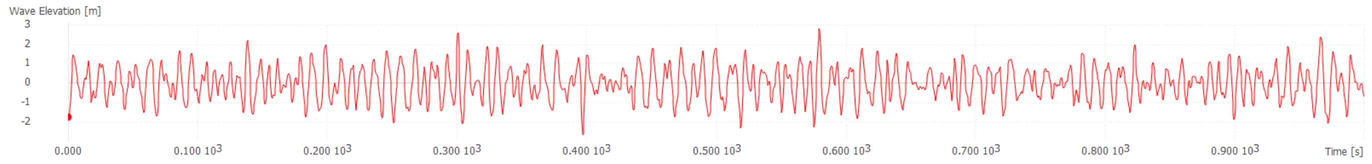


J. Saverin, S. Perez-Becker, R. B. D. Luna, D. Marten, J.-C. Gilloteaux and R. Kurnia, "D1.2. Higher Order Hydroelastic Module," 2021

Present QBlade Simulation



Wind velocity generated from TurbSim

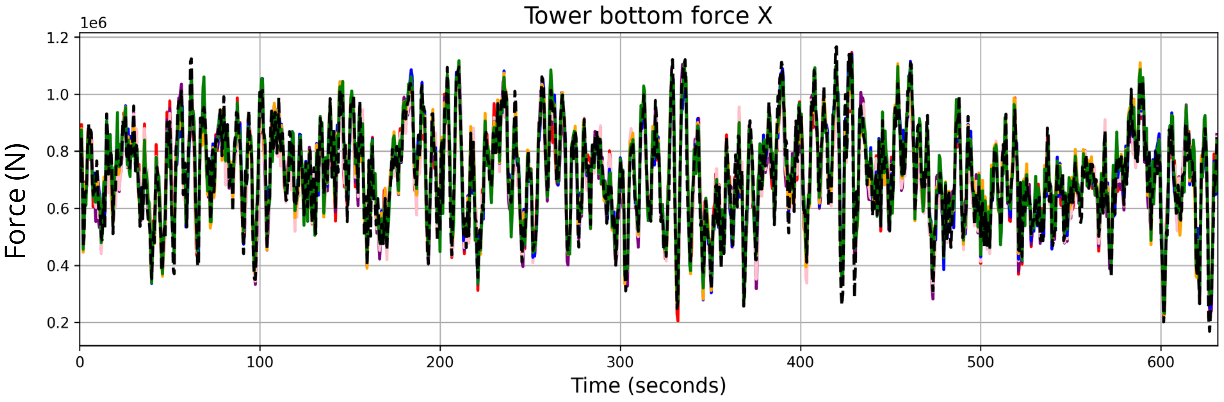


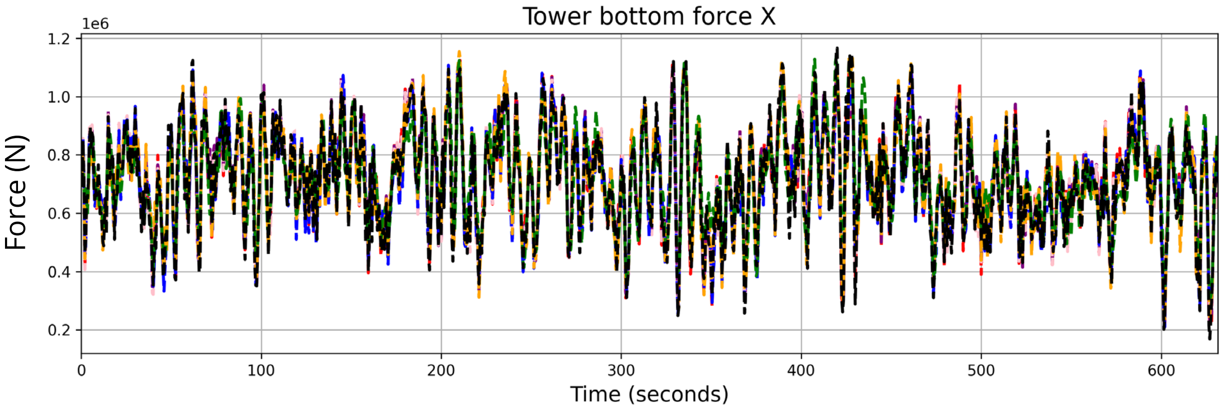
Wave elevation profile snapshot

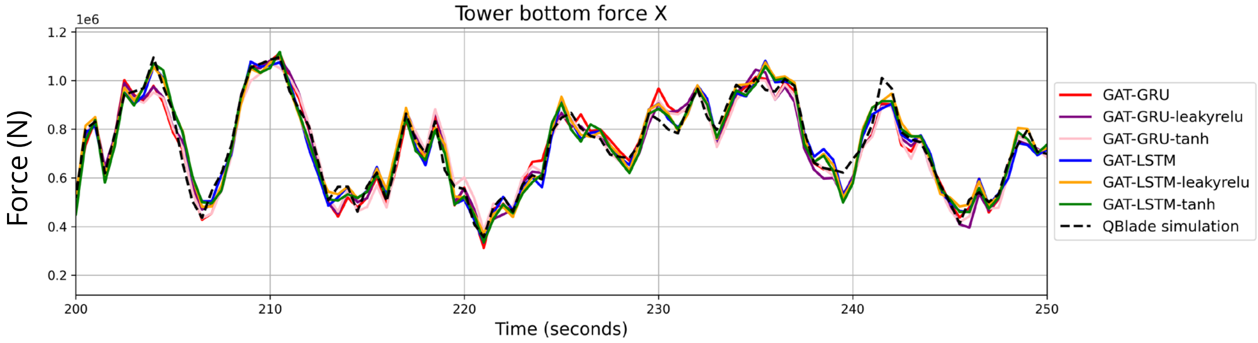
D. Marten, "Qblade," https://qblade.org/

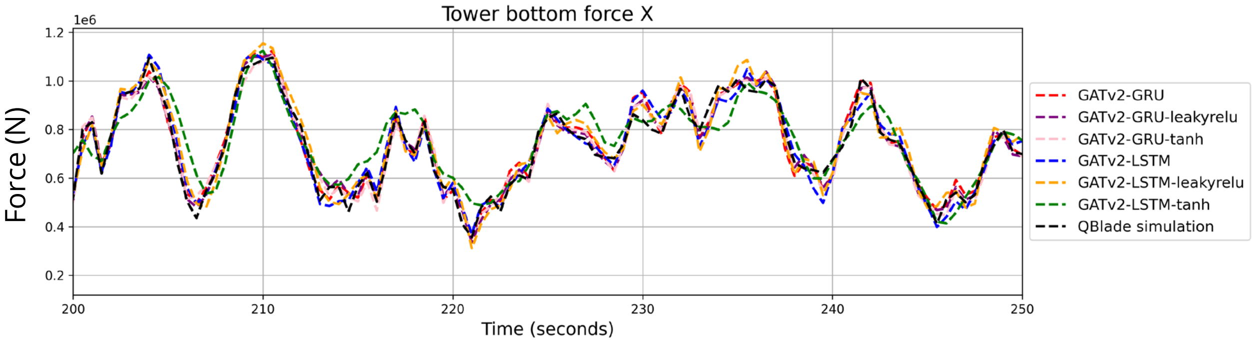
Physics-Guided Spatial-Temporal Graph Neural Network Prediction Results

GAT (force-aft) GATv2







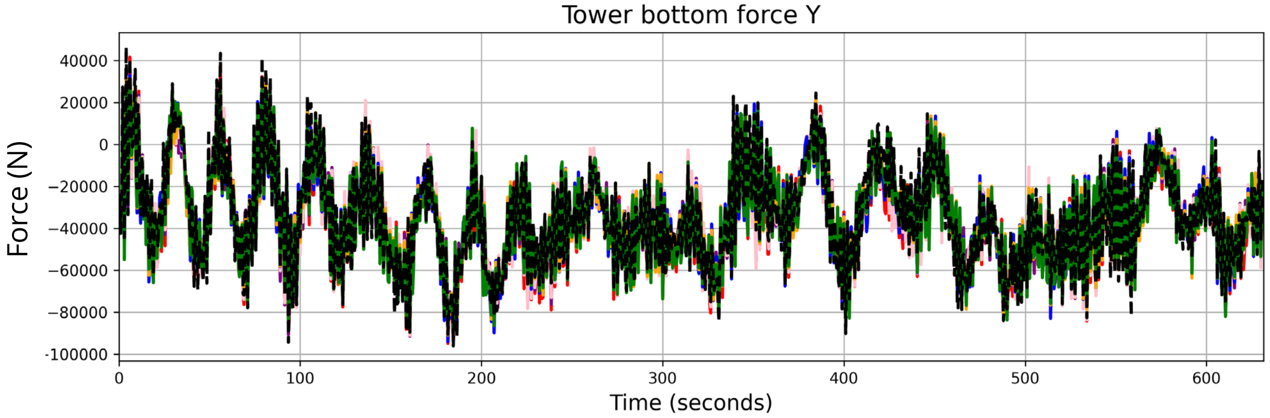


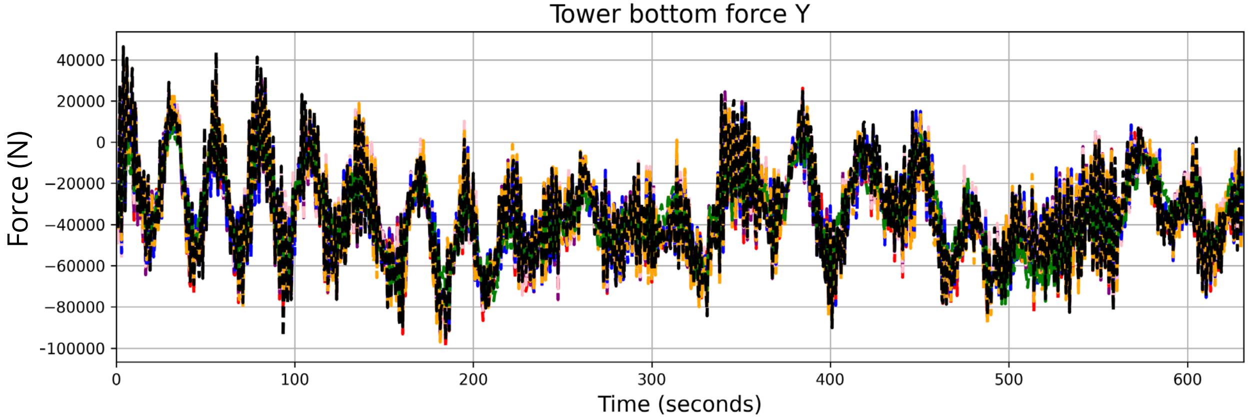
Physics-Guided Spatial-Temporal Graph Neural Network Prediction Results

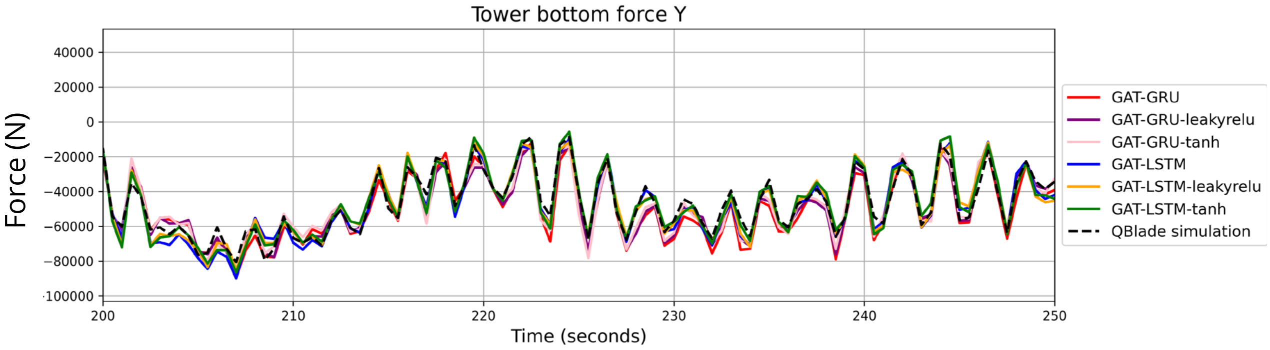
GAT

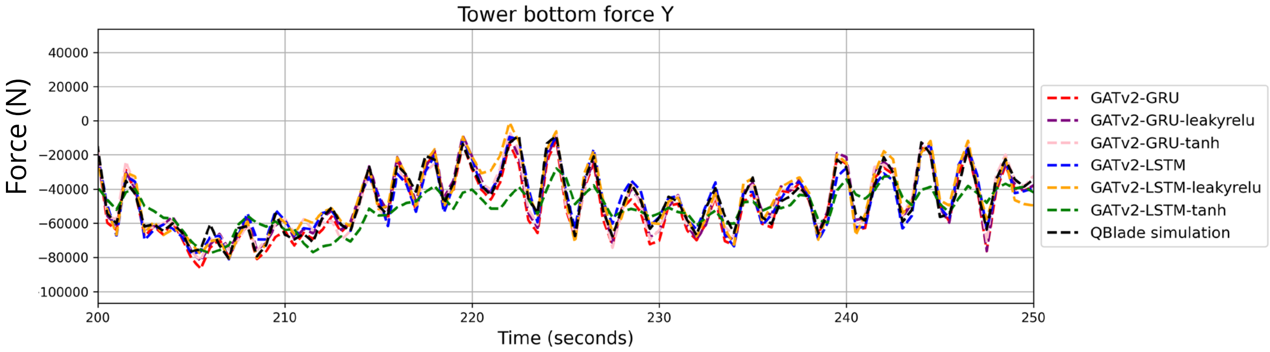
(side-side)

GATv2





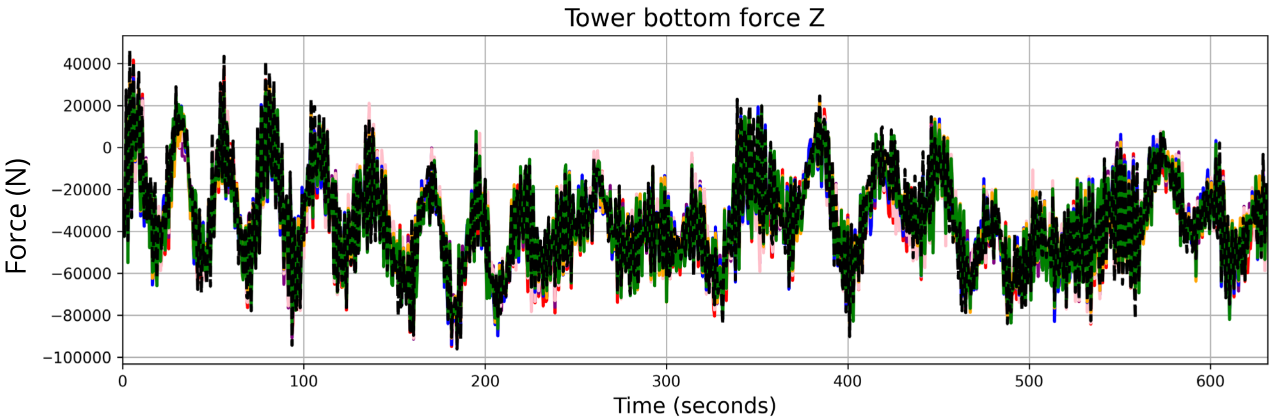


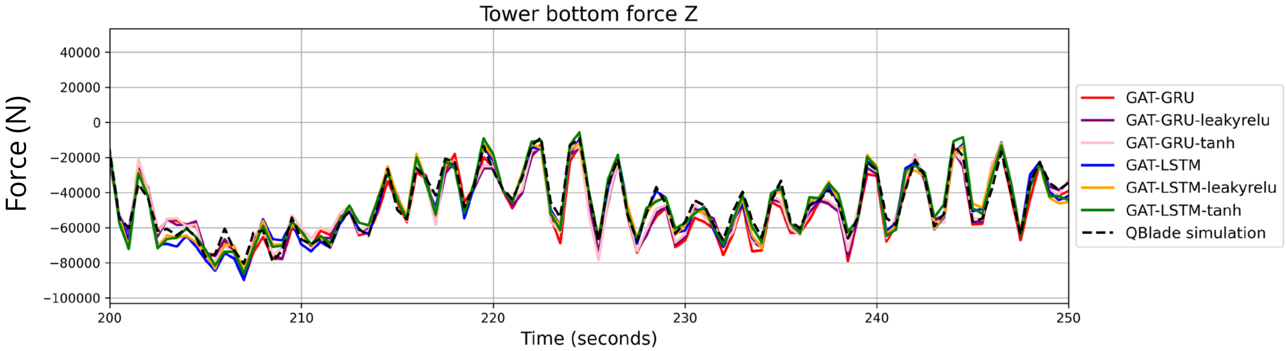


Physics-Guided Spatial-Temporal Graph Neural Network Prediction Results

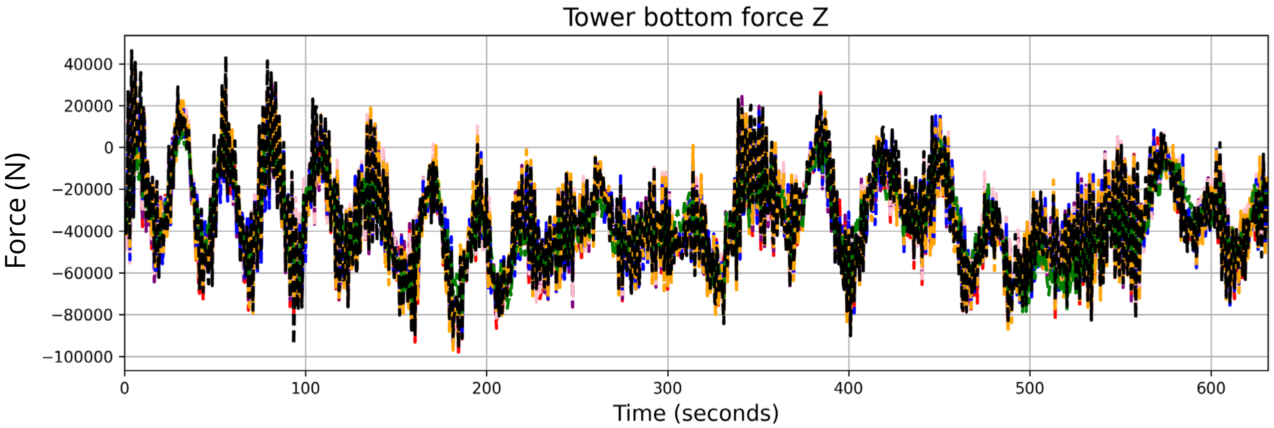
EERA DeepWind CONFERENCE 2025

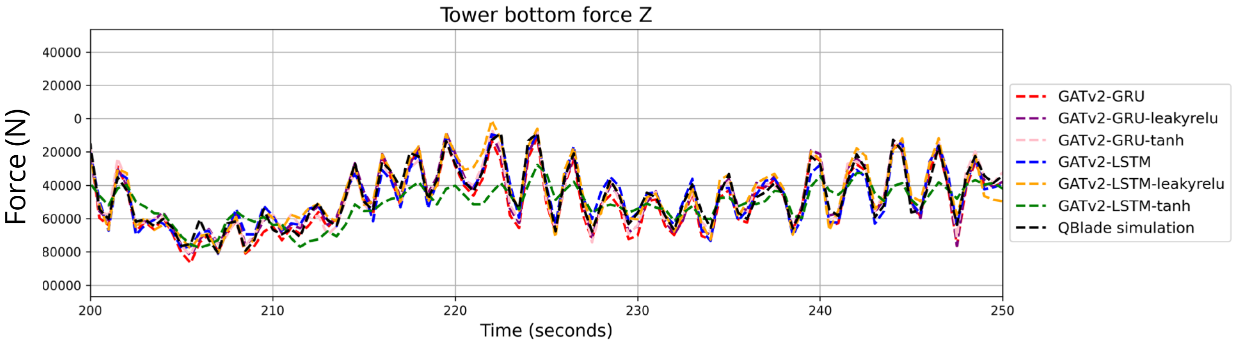
GAT





GATv2



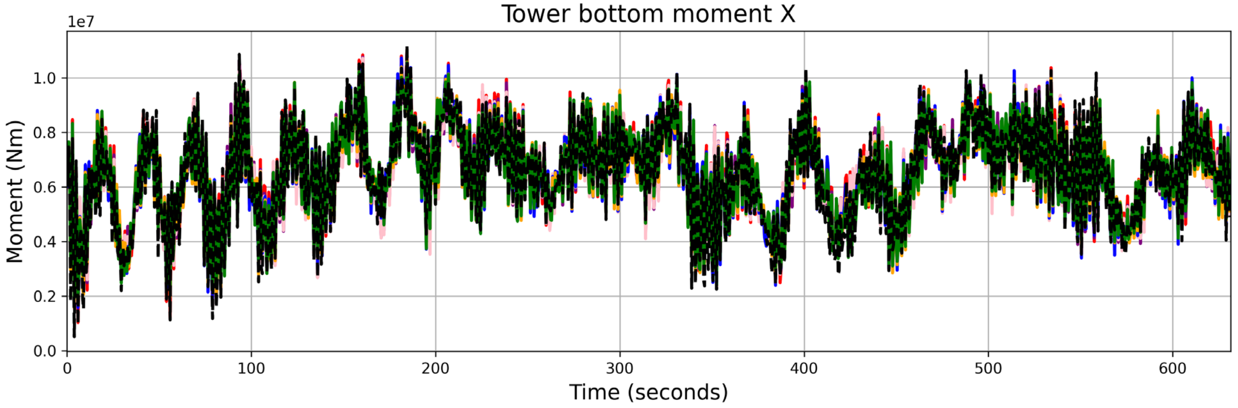


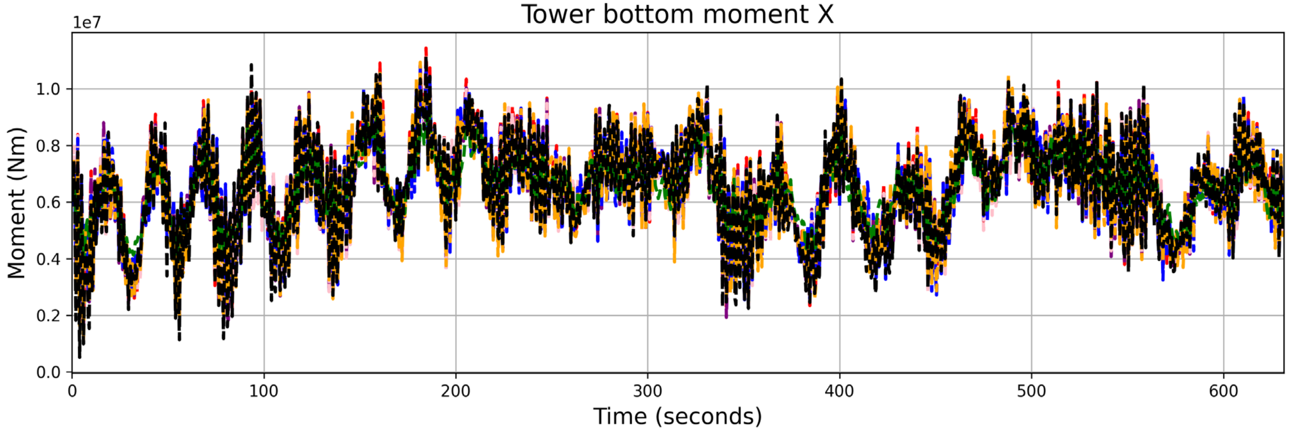
Physics-Guided Spatial-Temporal Graph Neural Network Prediction Results

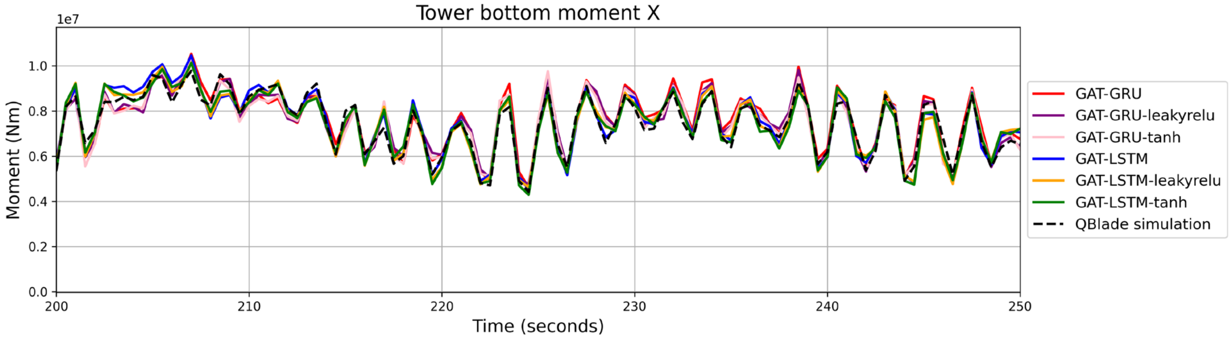
GAT

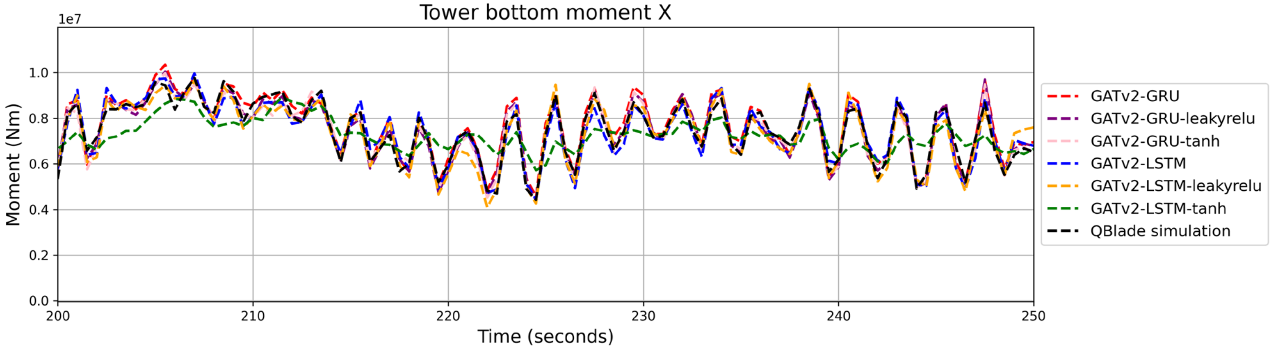
(side-side)

GATv2







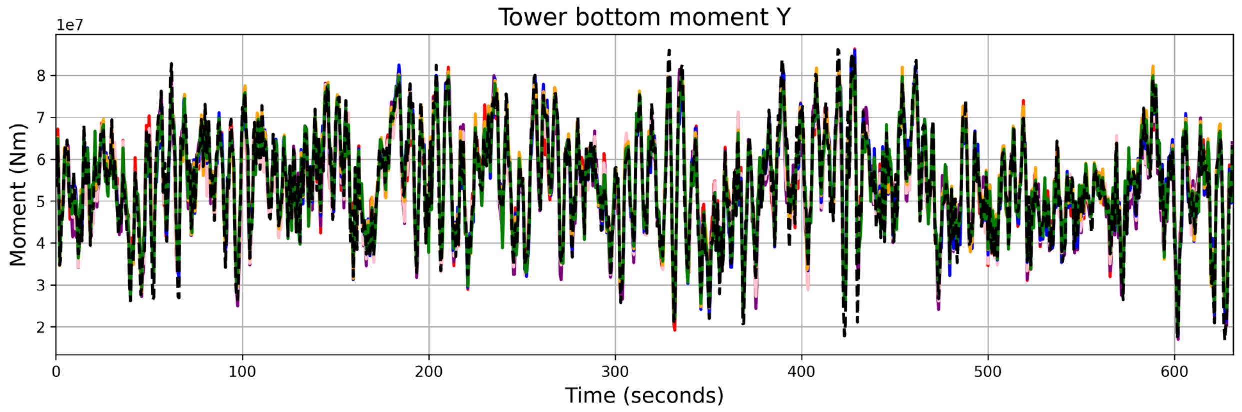


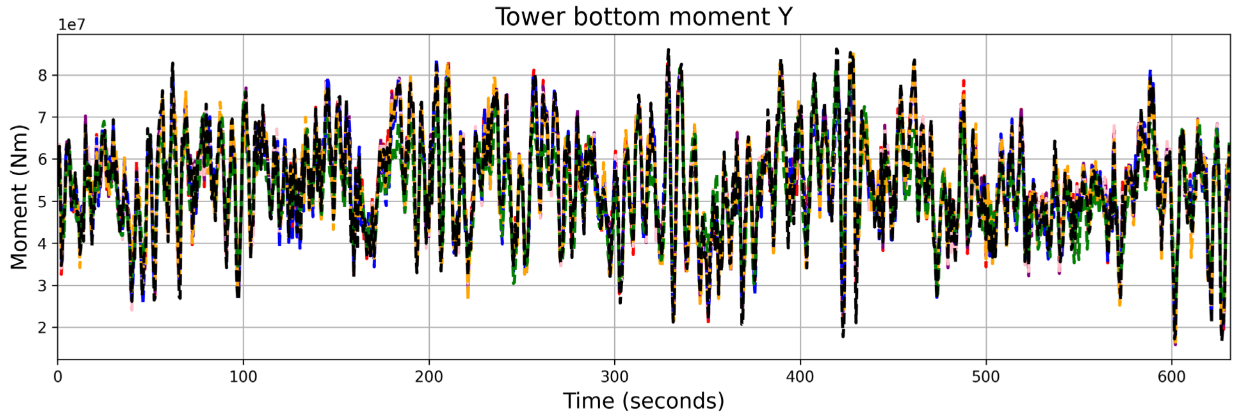
Physics-Guided Spatial-Temporal Graph Neural Network Prediction Results

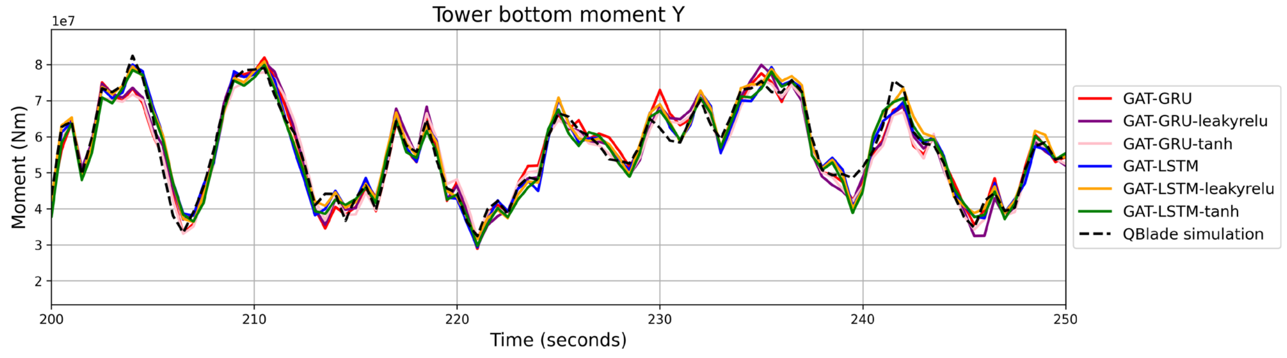
GAT

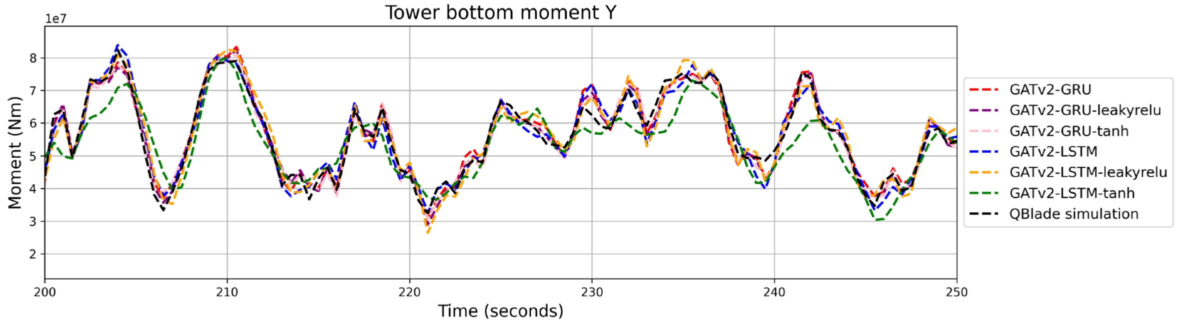
(force-aft)

GATv2



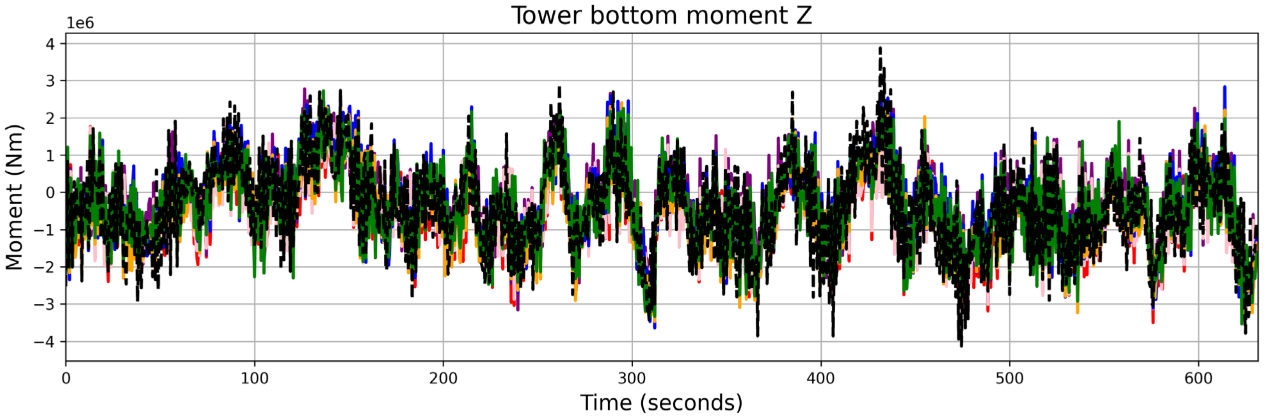


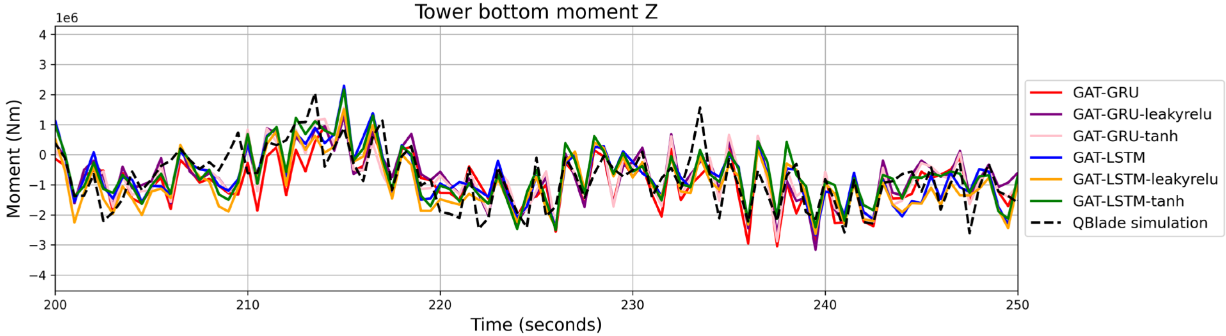




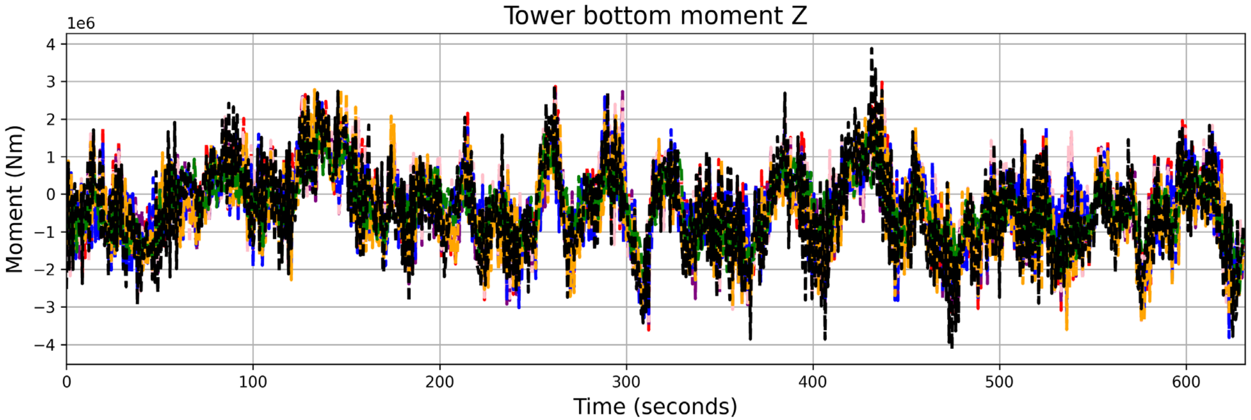
Physics-Guided Spatial-Temporal Graph Neural Network Prediction Results

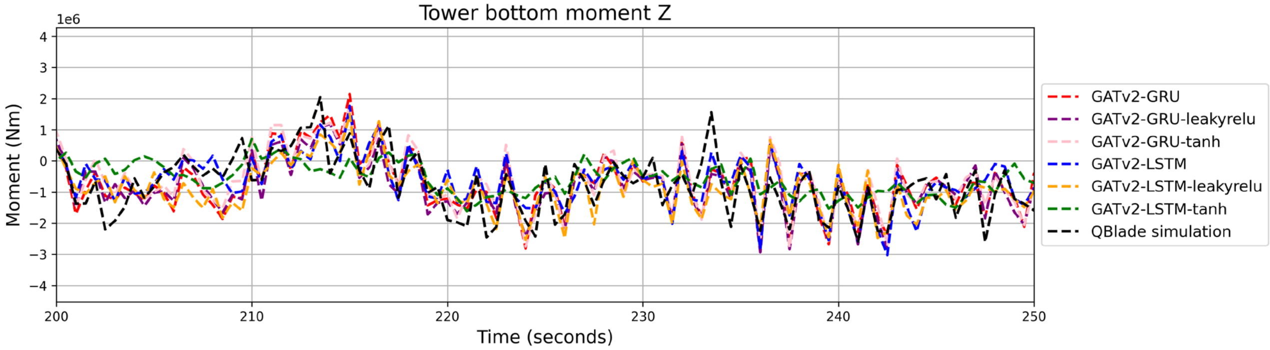
GAT





GATv2





Physics-Guided Spatial-Temporal Graph Neural Network Prediction Results

Percent Bias (PBIAS) (%)

	Force X	Forece Y	Force Z	Moment X	Moment Y	Moment Z	Average
GAT-GRU	-0.45	4.92	-0.04	1.63	-0.43	39.31	7.49
GAT-GRU-leakyrelu	-1.06	1.77	-0.18	0.48	-1.26	-29.82	-5.01
GAT-GRU-tanh	-0.99	-0.08	-0.25	-0.20	-1.47	31.10	4.69
GAT-LSTM	0.68	1.00	-0.05	0.41	0.53	-25.16	-3.77
GAT-LSTM-leakyrelu	0.96	0.88	0.10	0.34	1.21	25.40	4.82
GAT-LSTM-tanh	1.10	1.64	-0.21	0.65	0.57	-14.16	-1.74
GATv2-GRU	0.60	4.47	-0.04	1.68	0.46	-25.10	-2.99
GATv2-GRU-leakyrelu	1.22	0.27	0.03	-0.06	0.35	-3.27	-0.24
GATv2-GRU-tanh	0.56	-1.75	-0.17	-0.30	-0.14	-23.26	-4.18
GATv2-LSTM	0.01	1.03	-0.11	0.27	-0.09	-9.79	-1.45
GATv2-LSTM-leakyrelu	0.76	0.96	-0.07	0.21	-0.08	17.30	3.18
GATv2-LSTM-tanh	0.71	4.27	-1.39	0.21	-2.64	-5.47	-0.72

Great candidate models

Critical Force-aft and Side-side forces and moments

Conclusion

Novelty of new proposed Physics-Guided Spatial-Temporal Graph Neural Network:

- Directly address the highly nonlinear problem (especially second order hydrodynamics) and high dimensional system states under complicated load combination of wind, wave and current
- Explicitly include the physical properties and geometric properties as finite element modeling
- Physics-Guided training constraint included
- Excellent real-time tower force prediction performance (the best candidate model ±4% percentage error), average execution time 45s in CPU for 631.5s data (14 times faster)

THANK YOU

Kobe Hoi-Yin Yung

kobehy.yung@strath.ac.uk

EERA DeepWind CONFERENCE 2025