Toward Intelligent Monitoring and Digital Twins for Offshore Wind Turbines

As offshore wind energy expands, the demand for robust and scalable monitoring strategies becomes increasingly urgent. Turbines are exposed to complex and highly variable inflow conditions, including wake interactions and turbulent boundary layers, while operating in harsh marine environments with limited sensing infrastructure. This seminar presents a series of hybrid approaches to offshore wind monitoring and digital twin development, blending physics-based modeling with machine learning to extract actionable insights under data scarcity.

A suite of hybrid techniques is presented to estimate unmeasured quantities such as bending moments, aerodynamic loads, and turbine-induced dynamic responses using a minimal set of physical sensors. These methods integrate structural mechanics models with statistical learning algorithms to reconstruct virtual sensing outputs and propagate uncertainty throughout the inference pipeline. Focus is given to load estimation strategies and induced fatigue loading and damage accumulation in structural components like tower and foundation.

In addition to local monitoring, the framework supports population-level generalization through domain adaptation, transfer learning, and hierarchical Bayesian updating. These strategies enable the transition from individual turbine digital twins to scalable, cross-turbine models that enhance reliability and reduce monitoring costs across an entire fleet. The resulting framework facilitates decision-making for maintenance optimization, fault detection, and resilient system design under limited sensing infrastructure.

Demonstrative applications include real-world deployments at the jacket-based Block Island Wind Farm and two monopile-supported 6MW offshore wind farms currently operating in the U.S. and the North Sea. These case studies illustrate the accuracy and adaptability of the proposed monitoring and inference strategies across different structural typologies and environmental conditions. Results highlight how hybrid models, virtual sensing techniques, and physics-informed learning frameworks contribute to performance forecasting, damage detection, and life-cycle assessment. By integrating methods from structural dynamics, sensor fusion, and environmental modeling, this work supports the development of scalable, intelligent, and resilient offshore energy systems.



Eleonora Maria Tronci is an Assistant Professor in the Department of Civil and Environmental Engineering at Northeastern University. She received her second Ph.D. in 2022 from the Civil Engineering and Engineering Mechanics Department at Columbia University, after previously earning a Ph.D. in Structural Engineering from Sapienza University of Rome in 2019. She holds a M.S. and a Bachelor of Science in Structural and Civil Engineering from Sapienza University.

Her research focuses on structural health monitoring, machine learning, and transfer learning for civil and energy infrastructure systems. Her work integrates data-driven strategies, uncertainty quantification, and virtual sensing methodologies to enhance resilience in the face of evolving operational and environmental conditions. Over the years, she has pioneered advanced damage-

sensitive features extraction and modal identification techniques, and innovative transfer learning frameworks leveraging speech recognition models for structural damage detection.

Before joining Northeastern, Dr. Tronci was a Postdoctoral Scholar at Tufts University, where she worked on digital twinning and SHM of offshore wind turbines. Looking ahead, her research is expanding toward physics-informed machine learning, real-time monitoring strategies, and human-centered decision-making frameworks that integrate structural intelligence with actionable insights. Through these advancements, she aims to drive innovation in predictive modeling, adaptive control, and sustainable infrastructure management to support the next generation of resilient and high-performing energy systems.