A Generative AI-based Model for Real-time Prediction of Orbital Motions at the Tower-Top During Installation of Offshore Wind Turbines

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Abstract

Problem Statement: Offshore wind energy is expanding rapidly across the globe, with a notable shift toward utilizing larger turbines. These larger offshore wind turbines (OWTs) deliver higher energy output per rotation; however, they also bring additional complexities in installation due to their increased hub heights. Blade installation, in particular, is a highly demanding process where the blades are installed using crane vessels one at a time. The blade–hub mating process (*Figure 1a–1b*) represents the most critical phase [1] as it demands precise alignment between components. At this stage, the OWT is in the hammerhead configuration, with the monopile, transition piece, and nacelle already installed (*Figure 1c*). Due to an eccentricity between the tower axis and the center of gravity (COG) of the nacelle, wave-induced lateral motion of the nacelle results in torsional excitation about the tower axis. This eccentric loading couples lateral and longitudinal dynamics, giving rise to complex orbital motion at the tower-top (*Figure 1d*). If these orbital motions become excessive during blade mating, they may cause collisions at the blade root interface, installation delays, and increased safety hazards. Hence, there is a critical need for tools that can predict tower-top motion in real time to improve safety and operational efficiency during blade installation. In this context, digital twins, especially AI-driven models offer a promising approach to rapidly estimate motion responses and assist in real-time decision-making during offshore operations.

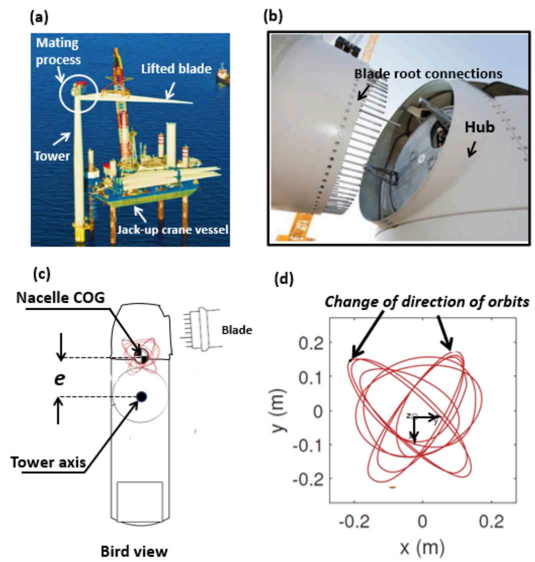

Figure 1: (a) OWT blade mating process using jack-up crane vessel [2] (b) Close-up view of blade root mating phase [3] (c) Top view: Hammerhead configuration of offshore wind turbine (d) Orbital motion of the nacelle COG during mating process

Aim of the Study: This study aims to design a digital twin (DT) of the OWT system that can predict orbital motions in real time across a range of scenarios in hammerhead configurations, thereby supporting informed decision-making during the installation process.

Methodology: The AI-driven digital twin (DT) model is developed using the latent diffusion model (LDM) framework, a type of generative AI architecture. LDMs apply the diffusion process—gradually adding and removing noise—not directly to raw data, but within a compressed latent space encoded by an autoencoder (AE) [4,5]. This approach also requires a reversible transformation between time series of the nacelle motion data and image representations used by the diffusion model. While existing methods such as Gramian Angular Fields (GSF/GDF) [6] and spectrograms offer ways to encode time-series data as images, they are not inherently reversible, limiting their utility for diffusion models in this application. To address this, a reversible variant of GSF is developed, adapted specifically for OWT motion. This approach incorporates input normalization and modified operations to support bidirectional conversion specifically for the OWT motion, enabling consistent recovery of both X and Y time-series data from synthesized images.

Data for Training and Validation: To train the LDM, generating a large amount of data is essential. The IEA 10 MW turbine [7] serves as the reference for this study, and a mathematical model of the installation system in the hammerhead configuration is developed in OrcaFlex. The tower and monopile are modeled as Timoshenko beam elements that account for axial, shear, bending, and torsional deflections. The nacelle is modeled as an eccentric point mass, rigidly attached to the topmost node of the tower. The model does not include any blades or controllers. A series of irregular wave load cases are applied to the model, and the corresponding motions of the nacelle in the fore-aft and side-side (X and Y directions) are recorded. The total recording duration is 1000s, of which the first 400s are discarded from the analysis to avoid transients. Each load case is repeated with several seeds since each realization of an irregular wave yields a unique time series, ultimately producing different motions at the tower-top. A total of 4500 data recordings were obtained, with 90% used for training and the remaining for validation.

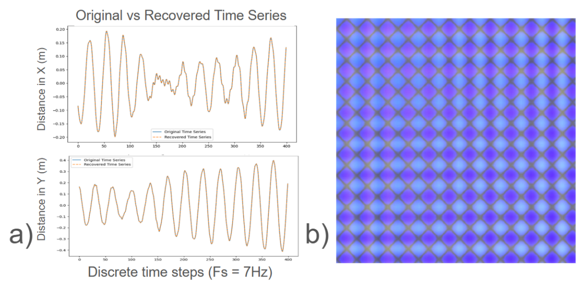

Figure 2: Image to time-series conversion results
a) Comparison between Original and recovered data showing full data recovery, **b)** Image representation

Results and Discussion: Several tests were run to demonstrate the effectiveness of the reversible GSF approach. The comparison in Figure 2 between the original and reconstructed signals shows that for a given set of X and Y signals, the data is able to be converted into an image and recovered with no error, proving the conversion is accurate. Following this, an AE was developed to compress image representations into a compact latent space. The AE demonstrates high reconstruction accuracy under stable motion conditions but shows reduced accuracy in high-frequency, unstable cases. Preliminary results for both image reconstruction and corresponding time-series recovery are presented in Figure 3 for both stable and unstable motion cases. Ongoing work is focused on improving AE robustness in unstable scenarios.

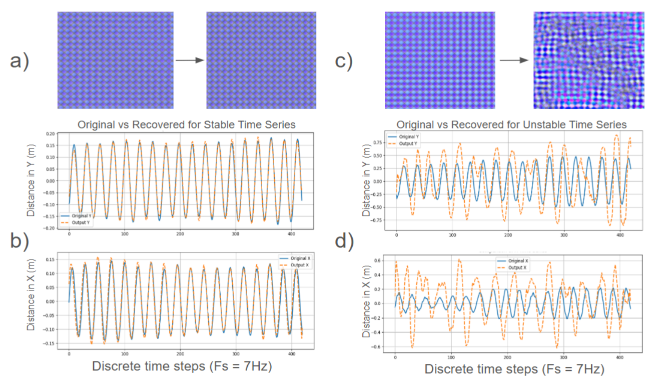

Figure 3: Auto-Encoder Results
a) Stable image comparison, **b)** Stable time-series comparison,
c) Unstable image comparison, **d)** Unstable time-series comparison

References:

[1] Verma, A.S., Jiang, Z., Ren, Z., Gao, Z. and Vedvik, N.P., 2019. *Energies*, *12*(10), p.1867.
[2]https://www.marinelog.com/offshore/renewables/grounded-wind-turbine-installation-barge-capsizes/
[3] https://www.power-technology.com/features/featureinpictures-longest-wind-turbine-rotor-blades.
[4] Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B., Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 10684–10695.
[5]https://milvus.io/ai-quick-reference/what-are-latent-diffusion-models-and-how-do-they-differ-from-pixelspace-diffusion
[6] Z. Wang and T. Oates, *arXiv preprint arXiv:1510.06104*, 2015.
[7] Bortolotti, P., Tarres, H.C., Dykes, K., Merz, K., Sethuraman, L., Verelst, D. and Zahle, F., 2019. IEA Wind TCP Task 37: Systems engineering in wind energy- WP2.1 Reference wind turbines.

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