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Transatlantic Forecasting and Spatial Yield Mapping of Co-Located Offshore Wind and Wave Energy Using Deep Learning: A Framework for Energy Optimization and Grid Integration

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Abstract

The co-location of offshore wind (OSW) and wave energy converters (WECs) offers a promising pathway to enhance power density and mitigate intermittency, yet the integrated planning and forecasting for such hybrid systems present significant challenges. This study introduces a novel, unified deep learning framework for forecasting hybrid energy output and assessing spatial yield potential across transatlantic regions. We analyze two distinct offshore sites: the *Borkum Riffgrund* wind farm in the German North Sea and the *Coastal Virginia Offshore Wind* (CVOW) zone in the U.S. Mid-Atlantic. The framework utilizes historical datasets from ERA5, NDBC, and DWD to train Long Short-Term Memory (LSTM) networks [1] for high-resolution, time-series energy forecasting [2, 3, 4]. This forecasting model is integrated with spatial yield mapping and techno-economic analysis to create a comprehensive toolchain for system optimization and grid-aware deployment. The comparative analysis demonstrates how regional climate differences dictate the strategic value of hybridization, providing critical insights for transatlantic energy planning.

Keywords: Offshore wind energy; Wave energy; Deep learning; Hybrid energy systems; Energy forecasting

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1 Introduction

The co-location of offshore wind (OSW) turbines and wave energy converters (WECs) is recognized as a key strategy for improving the output stability of marine renewable energy systems [5, 6, 7]. By harnessing complementary resources, hybrid systems can smooth power variability and optimize the use of shared electrical infrastructure. However, a significant challenge remains in developing integrated assessment tools that bridge the gap between resource forecasting, array layout optimization, and grid integration analysis.

This paper presents a unified computational framework that addresses this challenge. The core novelty lies in the end-to-end integration of spatiotemporal deep learning (DL) for forecasting, data-driven spatial yield mapping for initial site characterization, and techno-economic modeling for grid-aware feasibility assessment. We apply this framework in a comparative study of two strategically important transatlantic sites: the *Borkum Riffgrund* wind farm in the German North Sea and the *Coastal Virginia Offshore Wind* (CVOW) area in the U.S. Mid-Atlantic. As conceptually illustrated in Figure 1, the framework leverages historical data to produce actionable intelligence for hybrid energy project planning.

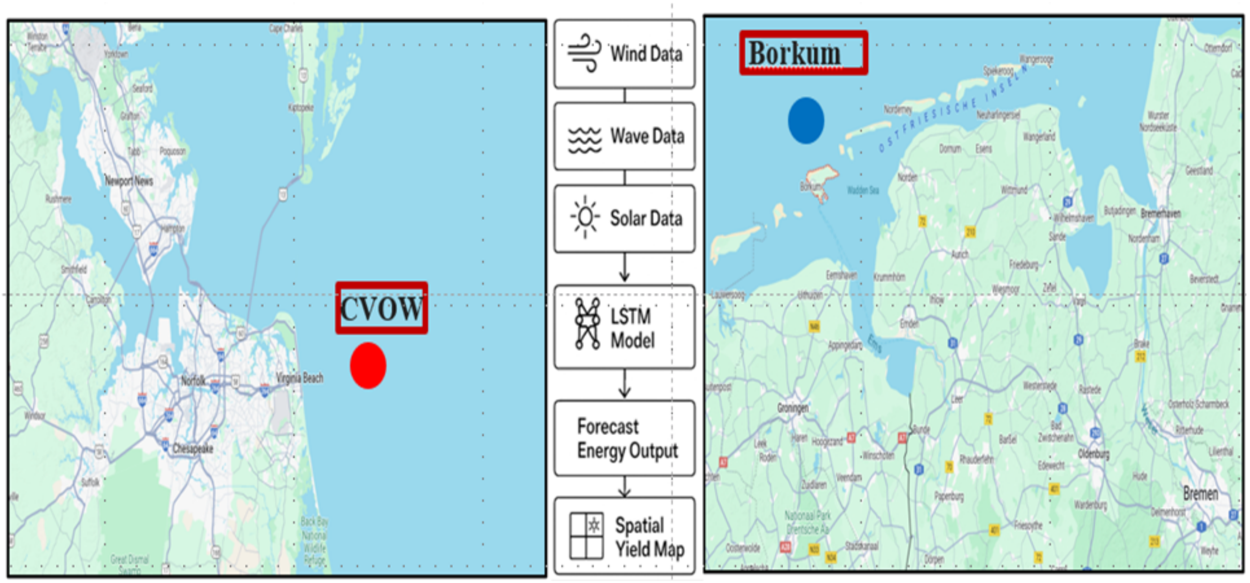

Figure 1: Conceptual overview of the proposed deep learning (DL) based forecasting framework. The study compares two offshore regions: the Coastal Virginia Offshore Wind (CVOW) site in the U.S. Mid-Atlantic (left, green marker) and the Borkum Riffgrund wind farm in the German North Sea (middle, red marker). Wind and wave data from both sites are fed into a deep learning model (LSTM) to forecast hybrid energy output, which is then used to generate spatial yield maps for planning and optimization.

The framework's output is interfaced with established tools like the NREL System Advisor Model (SAM) [8] to estimate Levelized Cost of Energy (LCOE) and assess financial viability. Furthermore, grid integration implications are evaluated in the context of regional transmission constraints, such as those identified in the U.S. DOE's Atlantic Transmission Study [9], providing a holistic assessment of a hybrid project's value.

2 Methodology

The framework comprises three interconnected components: data processing, hybrid power forecasting, and optimization analysis.

2.1 Data Sources and Site Characterization

The analysis is founded on a robust collection of historical meteorological and oceanographic data for the two study sites. Key data sources include:

- **ERA5 Reanalysis:** Hourly global data on wind speeds, significant wave height (H_s), and wave period (T_e) from ECMWF [10].
- **On-site Buoy Data:** High-frequency local measurements from the NDBC network (for CVOW) and DWD sources (for Borkum Riffgrund) for model validation and correction of coastal effects.
- **NREL Datasets:** Reference power curves for OSW turbines and WECs, along with cost and performance parameters for techno-economic modeling via SAM [8].

Each lease area is discretized into a high-resolution grid, with each cell containing site-specific data on bathymetry and long-term resource statistics.

2.2 Hybrid Power Forecasting via Deep Learning

The core of the forecasting module is a Long Short-Term Memory (LSTM) network, a recurrent neural network architecture proven for its efficacy in modeling temporal dependencies in time-series data [1, 2]. The LSTM is trained to predict the total hybrid power output, $P_{\text{hybrid}}(t)$, for a future time horizon (e.g., 1-24 hours). The total power for a farm with M turbines and N WECs is defined as:

$$P_{\text{hybrid}}(t) = \sum_{i=1}^{M} P_{\text{wind},i}(v_i(t)) + \sum_{j=1}^{N} P_{\text{wave},j}(H_{s,j}(t), T_{e,j}(t)) \tag{1}$$

where P_{wind} and P_{wave} are the device-specific power conversion functions. The wave power component is informed by the incident wave power flux, J, calculated according to IEC standards [11]:

$$J = \frac{\rho g^2}{64\pi} H_s^2 T_e \tag{2}$$

where ρ is seawater density and g is gravitational acceleration. The LSTM model learns the complex, non-linear mapping from meteorological inputs (v, H_s, T_e, direction) to the aggregated power output in Equation 1.

2.3 Spatial Yield Mapping and Layout Optimization

To guide layout decisions, the framework first generates **spatial yield maps**. For each grid cell in the lease area, the potential Annual Energy Production (AEP) of a co-located turbine-WEC unit is computed using the long-term time-series data. This produces a high-resolution map of energy "hotspots," providing a data-driven initial assessment that complements computationally intensive optimization routines [12].

This map informs a subsequent multi-objective layout optimization process. The objective function seeks to simultaneously (1) maximize total AEP, (2) minimize LCOE, and (3) minimize output variability, particularly by penalizing high-magnitude power ramp rates.

3 Techno-Economic and Grid Integration Analysis

The forecasted power time series and optimized layouts are fed into a techno-economic and grid integration analysis module. Using NREL's SAM [8], we calculate project LCOE, comparing hybrid scenarios against a wind-only baseline to quantify the economic trade-offs between higher capital expenditure and increased capacity factor or reduced grid service costs.

Grid integration value is assessed by analyzing the statistical properties of the aggregated power output. A primary metric is the power **ramp rate (RR)**, defined as the change in power over a time interval Δt:

$$RR(t) = \frac{P(t + \Delta t) - P(t)}{\Delta t} \tag{3}$$

The framework analyzes the distribution of ramp rates to quantify the smoothing effect of hybridization. A reduction in the frequency and magnitude of extreme ramps translates directly to enhanced grid stability and potentially lower operational costs for system operators. This analysis is contextualized by regional grid characteristics, such as the transmission constraints detailed in the DOE's Atlantic study [9].

4 Conclusion

This paper presents a rigorous, integrated framework for the analysis of co-located offshore wind and wave energy systems. The novelty of the approach resides in its unification of deep learning-based forecasting with spatial, economic, and grid-centric analyses, creating a powerful toolchain for project development.

The transatlantic comparative study demonstrates that the strategic benefit of hybridization is highly dependent on regional climatology. For the U.S. Mid-Atlantic, the value lies in mitigating seasonal resource intermittency, leading to a higher year-round capacity factor. For the German North Sea, the primary benefit is in smoothing short-term variability and enhancing output during extreme weather events. These findings have direct implications for grid planning and technology deployment strategies, suggesting that hybrid systems can reduce the need for costly grid reinforcements and ancillary services [7, 9].

Ultimately, this work provides an AI-augmented methodology essential for the strategic design, optimization, and de-risking of next-generation hybrid offshore energy systems. The framework is adaptable and provides the quantitative foundation needed to advance co-located projects from concept to commercial viability.

References

[1] S. Hochreiter and J. Schmidhuber. "Long short-term memory". In: *Neural Computation* 9.8 (1997), pp. 1735–1780.

[2] J. Wang et al. "A review of wind speed and wind power forecasting with deep learning models". In: *Applied Energy* 304 (2021), p. 117766.

[3] Y. Qin et al. "A dual-stage attention-based recurrent neural network for time series prediction". In: *Proceedings of the 26th International Joint Conference on Artificial Intelligence (IJCAI)*. AAAI Press, 2017, pp. 2627–2633.

[4] C. Zhang et al. "Deep learning for spatio-temporal data mining: A survey". In: *IEEE Transactions on Knowledge and Data Engineering* 11 (2019), pp. 1–1.

[5] S. Astariz and G. Iglesias. "Co-located wave-wind farms: Economic assessment as a function of layout". In: *Energy* 91 (2015), pp. 483–495.

[6] J. Fernandez-Chozas, J. P. Kofoed, and M. Kramer. "Hybrid floating wind and wave energy systems: Reviewing the research trends and challenges". In: *Journal of Marine Science and Engineering* 9.6 (2021), p. 617.

[7] H. Del Pozo, C. P'erez-Collazo, and G. Iglesias. "Co-located wind-wave farms: Optimal control and grid integration". In: *Energy* 272 (2023), p. 127176.

[8] NREL. *System Advisor Model (SAM) for Marine Energy*. 2024. URL: https://sam.nrel.gov/marine-energy.html.

[9] U.S. Department of Energy. *Atlantic Offshore Wind Transmission Study*. 2023. URL: https://www.energy.gov/gdo/atlantic-offshore-wind-transmission-study.

[10] H. Hersbach et al. "The ERA5 global reanalysis". In: *Quarterly Journal of the Royal Meteorological Society* 146.730 (2020), pp. 1999–2049.

[11] IEC. *TS 62600-101: Marine energy–Wave, tidal and other water current converters–Part 101: Wave energy resource assessment and characterization*. Tech. rep. International Electrotechnical Commission, 2015.

[12] C. Teixeira-Duarte, V. S. Neary, and B. Zanuttigh. "Layout optimization of co-located wind-wave farms: A multi-objective approach". In: *Applied Ocean Research* 118 (2022), p. 102987.