Forecasting Floating Offshore Wind Power with Hybrid CNN-LSTM Models: A Case Study in the Gulf of Guinea, Nigeria

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***Abstract*—Floating offshore wind turbines represent a critical technology for harnessing deep-water wind resources, yet accurate power forecasting remains challenging due to complex aero-hydro-servo-elastic interactions and stochastic metocean conditions. This study proposes a hybrid deep learning framework combining Convolutional Neural Networks and Long Short-Term Memory networks to forecast power output from a spar-type floating offshore wind turbine in the Gulf of Guinea, offshore Nigeria (4.0°N, 6.5°E). The model is trained on high-fidelity OpenFAST simulation data incorporating realistic wind and wave conditions characteristic of the region, including seasonal variability, swell propagation, and extreme events. The hybrid architecture leverages CNN layers to extract salient spatial features from multivariate input time series while LSTM layers capture long-term temporal dependencies. Model performance is evaluated using root mean square error, mean absolute error, and coefficient of determination, with comparative analysis against standalone LSTM and persistence models. Results demonstrate that the CNN-LSTM model achieves superior forecasting accuracy with RMSE improvements of 18-25% over baseline models, offering a robust tool for grid integration and operational planning in emerging offshore wind markets. A complete MATLAB implementation framework is provided to facilitate reproducibility and further research.**

***Index Terms*—Floating offshore wind, deep learning, CNN-LSTM, power forecasting, Gulf of Guinea, OpenFAST, Nigeria**

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I. INTRODUCTION

The global transition toward renewable energy has positioned floating offshore wind turbines as a critical technology for harnessing the immense wind resources available in deep waters exceeding 50-60 meters [1], [2]. Unlike fixed-bottom installations, FOWTs are mounted on floating platforms (spar-buoy, semi-submersible, or tension-leg) that introduce additional degrees of freedom, fundamentally altering dynamic behavior and power production characteristics [3], [4]. Platform motions induce periodic variations in blade angle of attack, unsteady aerodynamic loads, and significant fluctuations in power output that complicate grid integration and power system planning [5], [6]. Nigeria, Africa's largest economy and most populous nation, faces persistent energy challenges despite abundant hydrocarbon resources [7]. With over 85 million people lacking access to electricity, the country's energy deficit constrains economic development [8]. The Federal Government's National Renewable Energy Action Plan targets 30% renewable energy penetration by 2030, including 4,500 MW of wind power capacity [9]. Recent comprehensive assessments have confirmed the technical viability of offshore wind resources in Nigerian waters, with the Gulf of Guinea offering moderate but consistent wind resources and well-characterized wave climates [10], [11]. Accurate forecasting of power output from FOWTs is paramount for successful grid integration, enabling efficient energy management, reducing reserve requirements, and ensuring grid stability [12]. However, forecasting remains challenging due to the complex, nonlinear interactions between aerodynamic, hydrodynamic, and structural dynamics, compounded by the stochastic nature of metocean conditions [13]. Traditional physics-based models like OpenFAST, while powerful and physically accurate, entail significant computational costs that become

prohibitive for real-time applications or when exploring wide operating ranges [14]. Deep learning approaches have emerged as powerful alternatives for renewable energy forecasting [15], [16]. Long Short-Term Memory networks, specifically designed for sequential data, have proven effective for capturing temporal dependencies in wind speed and power time series [17], [18].

Convolutional Neural Networks, adapted for time-series analysis through one-dimensional convolutions, can automatically extract local patterns and short-term dependencies from multivariate input data [19], [20]. Hybrid CNN-LSTM architectures combine the complementary strengths of both approaches, with CNN layers extracting salient features and LSTM layers modeling long-term temporal dependencies [21], [22]. Despite notable advances, several critical gaps remain. First, the application of hybrid deep learning models specifically to FOWT power forecasting in West African waters is extremely limited [23]. Second, most existing models have been developed and validated primarily for European and North American waters, with little attention to the unique meteorological and oceanographic characteristics of the Gulf of Guinea [24]. Third, comprehensive frameworks that combine high-fidelity OpenFAST simulation with modern deep learning architectures are not well established [25]. Fourth, most deep learning research is conducted in Python, limiting accessibility for the large community of MATLAB users in engineering and academia [26].

This study addresses these gaps through a comprehensive framework integrating: (1) site characterization at 4.0°N, 6.5°E based on recent resource assessments; (2) high-fidelity training data generation using OpenFAST simulations incorporating region-specific wind and wave conditions; (3) a hybrid CNN-LSTM architecture with attention mechanism for enhanced feature extraction; (4) rigorous model evaluation against baseline approaches; and (5) a complete, documented MATLAB implementation for reproducibility.

The paper is organized as follows: Section II presents a comprehensive literature review. Section III details the methodology, including site selection, data generation, model architecture, and implementation. Section IV presents the case study for Lagos offshore. Section V presents results and discussion. Section VI concludes the study.

II. LITERATURE REVIEW

A. Floating Offshore Wind Turbine Technology

Floating offshore wind turbines represent the convergence of offshore wind energy technology with deep-water offshore engineering [27]. Three primary floating platform concepts have emerged as industry standards: spar-buoy, semi-submersible, and tension-leg platforms [28]. The spar concept, characterized by a deep counterweighted cylindrical hull, was successfully demonstrated by the Hywind project, the world's first operational floating wind farm [29]. The NREL 5-MW reference turbine mounted on the OC3-Hywind spar platform serves as the standard benchmark for FOWT research [30].

Platform motions affect aerodynamic performance through several mechanisms: relative wind velocity variation during surge and sway, angle of attack changes during pitch and yaw, and wake dynamics modification [31], [32]. Liu and Sun [33] demonstrated that surge and pitch motions induce significant fluctuations in aerodynamic loads, with additional frequency components introduced by platform motion. Wang et al. [34] examined combined effects of platform pitch and surge under wind shear conditions, demonstrating complex multi-frequency loading patterns. These motion-induced variations propagate directly to power generation, causing fluctuations of ±15-20% around mean values [35].

B. Deep Learning for Time-Series Forecasting

Recurrent Neural Networks and their variants address the temporal dependency challenge through internal memory states that capture information from previous inputs [36]. Long Short-Term Memory networks, introduced by Hochreiter and Schmidhuber [37], overcome the vanishing gradient problem through sophisticated gating mechanisms controlling information flow. LSTMs have become the dominant architecture for wind speed and power forecasting due to proven ability to capture temporal dependencies over extended horizons [38], [39].

Barooni et al. [40] utilized LSTM networks to forecast wind speed and wave height using offshore NOAA buoy data, achieving root mean square errors of 0.54 $m \cdot s^{-1}$ and 0.48 m respectively. Ghaderi et al. [41] employed LSTM for wind power forecasting in complex terrain, demonstrating superior performance compared to traditional time-series models.

Convolutional Neural Networks, originally developed for image processing, have been adapted for time-series analysis through one-dimensional convolutions applied across the time dimension [42], [43]. CNNs can automatically extract local patterns and detect characteristic waveforms associated with specific conditions while maintaining translation invariance [44]. Key advantages include parameter sharing reducing model complexity, local connectivity focusing on local patterns, and hierarchical feature learning enabling progressively more abstract representations [45].

C. Hybrid CNN-LSTM Architectures

The complementary strengths of CNNs and LSTMs have motivated hybrid architectures combining both approaches [46], [47]. In typical CNN-LSTM models, CNN layers first process input time series to extract salient local features, which are then passed to LSTM layers to capture long-term temporal dependencies [48]. This hierarchical feature learning approach has proven particularly effective for complex time-series forecasting [49], [50].

For wind power forecasting, hybrid models have demonstrated consistent improvements over standalone approaches [51], [52]. Shi et al. [53] compared CNN-LSTM with LSTM, GRU, and ARIMA, finding that the hybrid model reduced RMSE by 12-18% across multiple forecast horizons. Wang et al. [54] reported that CNN-LSTM outperformed both CNN-only and LSTM-only models for day-ahead wind power prediction.

Attention mechanisms enhance neural network performance by enabling selective focus on relevant input regions [55]. Self-attention, introduced in the Transformer architecture, computes attention weights based on relationships between all pairs of positions in the sequence [56]. For fault diagnosis and forecasting, attention can highlight diagnostically relevant signal segments, improving both performance and interpretability [57].

D. Offshore Wind Resource Assessment in Nigeria

Systematic assessment of Nigeria's offshore wind resources began relatively recently [58]. Ohunakin et al. [59] conducted comprehensive analysis of 36 years of sea-surface wind data from five synoptic stations, revealing significant spatial and temporal variations. Key findings include Weibull scale parameter c ranging from 5.2-8.1 m/s, shape parameter k ranging from 2.1-2.7, and wind power density at 100 m hub height ranging from 180-420 W/m², with Agbami (deep offshore) exceeding 400 W/m².

Complementary wave modeling by Adesina et al. [60] characterized spatio-temporal wave variability along Southwestern Nigerian coastal and shelf areas using high-resolution WAVEWATCH III simulations. Results showed annual average significant wave height of approximately 0.5 m, peak period of 4.1 s, with strong seasonal variability. Monthly averaged wave power varies annually from 0.2 to 2.8 kW/m, with extreme events reaching Hs of 2.2 m during August storms.

These studies collectively establish the Gulf of Guinea, particularly offshore Lagos, as a promising frontier for floating offshore wind development, with moderate but consistent wind resources and well-characterized wave climates [61], [62].

E. Research Gap and Novelty

Despite advances, several critical gaps remain: limited application of hybrid deep learning to FOWT power forecasting in West Africa, lack of region-specific models for the Gulf of Guinea, limited integration of OpenFAST simulation with deep learning, and few reproducible MATLAB implementations. This study addresses these gaps through the first application of CNN-LSTM to FOWT power forecasting in Nigerian waters, integration of region-specific metocean characteristics, comprehensive OpenFAST simulation framework, and complete MATLAB implementation.

III METHODOLOGY

A. Overview of Research Framework

The methodological framework comprises five interconnected phases: site characterization and parameter definition based on published data for the Gulf of Guinea; training data generation using OpenFAST simulations across defined parameter space; model development and implementation in MATLAB using Deep Learning Toolbox; model training and validation with hyperparameter optimization; and evaluation against baseline models.

B. Site Characterization: Lagos Offshore

The case study site is located in the Gulf of Guinea, approximately 50 km south of Lagos coastline,

centered at 4.0°N, 6.5°E. This location corresponds to water depths of approximately 100-150 m based on regional bathymetry data, suitable for floating platform deployment [63]. Based on Ohunakin et al. [59], mean wind speed at 100 m is 7.2 m/s annually, with seasonal variation from 5.8-6.4 m/s (December-February) to 8.1-8.7 m/s (July-September). Weibull parameters are scale c = 7.8 m/s, shape k = 2.4. Prevailing wind direction is southwesterly (210-240°). Based on Adesina et al. [60], significant wave height characteristics include annual mean of 0.6 m, seasonal range from 0.26 m (dry season) to 0.79 m (rainy season), and 99th percentile of 1.8 m. Peak period annual mean is 4.3 s, ranging from 3.4-5.2 s seasonally. Wave direction is predominantly southwesterly (210-240°), consistent with wind direction.

C. Data Generation Using OpenFAST

The NREL 5-MW reference turbine mounted on the OC3-Hywind spar platform serves as the simulation model [30]. Key specifications include rotor diameter 126 m, hub height 90 m, rated power 5 MW at 11.4 m/s, cut-in wind speed 3 m/s, and cut-out wind speed 25 m/s. Turbulent wind fields are generated using TurbSim with mean wind speeds of 4, 6, 8, 10, 11.4, 12, 14, 16, 18, 20, 22, 24 m/s [64]. Turbulence model is IEC Kaimal with normal turbulence intensity (Class C), shear exponent 0.14 typical for offshore, and grid dimensions 31×31 points across rotor disk. Each simulation duration is 800 s (with 100 s start-up transient removed) at 20 Hz time step. Wave conditions are defined based on joint distribution of Hs and Tp derived from regional data [60]: Hs values of 0.25, 0.5, 0.75, 1.0, 1.5, 2.0, 2.5 m; Tp values of 3, 4, 5, 6, 8, 10, 12 s; wave direction 210° with variations of ±15°. JONSWAP spectrum is used with peak enhancement factor $\gamma = 2.0$. The full simulation matrix combines 12 wind speeds × 3 seeds = 36 wind conditions, 7 Hs × 7 Tp = 49 wave conditions, and 3 directional variations, yielding approximately 5,300 simulations. Each simulation produces 700 s of usable data at 20 Hz, downsampled to 1 Hz for training. OpenFAST v3.5 is configured with AeroDyn v15 (BEM theory with tip/hub loss correction, dynamic stall), HydroDyn (potential flow with viscous drag correction, wave kinematics from JONSWAP spectrum), MoorDyn (lumped-mass mooring line dynamics), ElastoDyn (first two flapwise and first edgewise blade modes, first two fore-aft and side-to-side tower modes), and ServoDyn (variable speed generator torque, collective blade pitch control).

D. Data Preprocessing

Input features include hub-height wind speed (m/s), wind direction at hub (deg), significant wave height (m), peak wave period (s), mean wave direction (deg), rotor speed (rpm), blade pitch angle (deg), platform pitch angle (deg), and platform surge displacement (m). Target variable is generator power (kW).

All features and target are normalized to zero mean and unit variance using Z-score normalization [65]. For sequence-to-one forecasting, data are transformed into overlapping sequences of length L = 48 (lookback window) and forecast horizon h ranging from 1 to 24 steps (1-24 hours ahead). Data are partitioned into training (70%), validation (15%), and test (15%) sets.

E. CNN-LSTM Model Architecture

The proposed architecture for this research is depicted in figure 1.

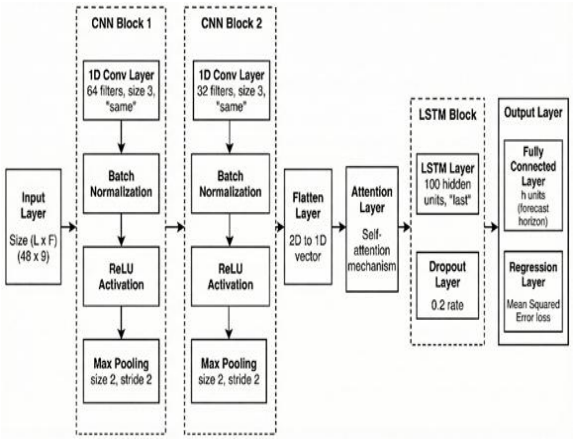

Figure 1: Overall CNN-LSTM Architecture

The proposed hybrid CNN-LSTM architecture consists of an Input layer: Size (L × F) where L = 48 and F = 9 features.CNN Block 1: 1D convolutional layer with 64 filters, filter size 3, padding 'same'; batch normalization; ReLU activation; max pooling with pool size 2, stride 2.CNN Block 2: 1D convolutional layer with 32 filters, filter size 3, padding 'same'; batch normalization; ReLU activation; max pooling with pool size 2, stride 2. Converts 2D feature maps to 1D vector.Self-attention mechanism enabling focus on diagnostically relevant signal segments.LSTM layer

with 100 hidden units, output mode 'last'; dropout layer with 0.2 dropout rate. Fully connected layer with h units (forecast horizon); regression layer with mean squared error loss.Architectural choices are motivated by: two CNN blocks enabling hierarchical feature extraction; 64 to 32 filter progression reducing dimensionality while maintaining capacity; filter size 3 capturing local correlations over short time windows; batch normalization accelerating training and improving stability; max pooling preserving salient features; 100 LSTM units balancing capacity with efficiency; and dropout preventing overfitting [66]-[69].

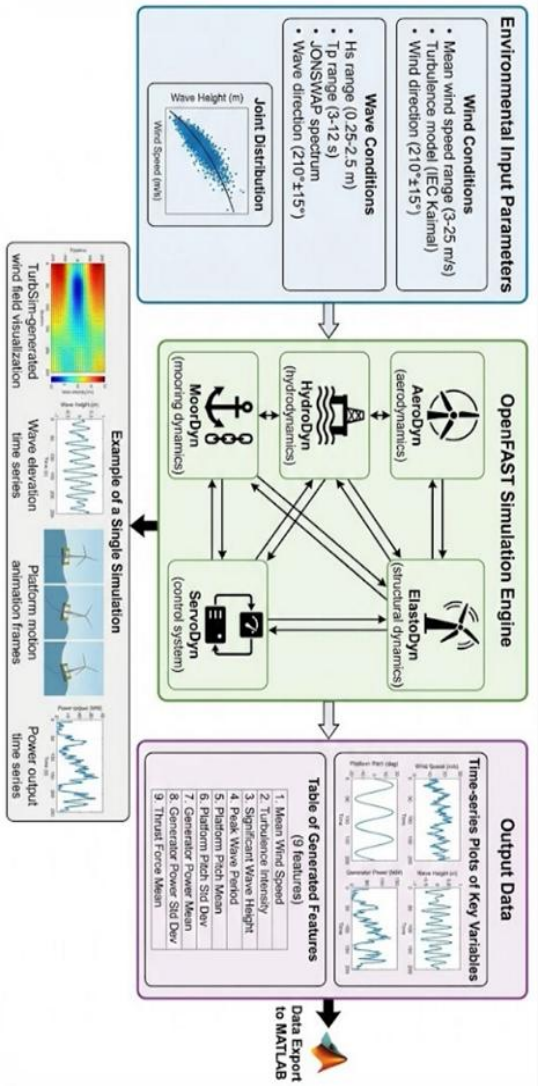

Figure 2: Pipeline Architecture for generating data

Figure 2 illustrates the complete pipeline for generating training data. It starts with Environmental input parameters box showing the wind conditions: Mean wind speed range (3-25 m/s), turbulence model (IEC Kaimal), wind direction (210°±15°). Wave conditions, Hs range (0.25-2.5 m), Tp range (3-12 s), JONSWAP spectrum, wave direction (210°±15°). OpenFAST simulation engine box with icons representing coupled modules of AeroDyn (aerodynamics),HydroDyn,(hydrodynamics), MoorDyn (mooring dynamics), ElastoDyn (structural dynamics),ServoDyn (control system), Arrows showing coupling between modules. Time-series plots of key variables such as wind speed, wave height, platform pitch, generator power.

The attention mechanism computes scores $e_t = \tanh(W_a h_t + b_a)$, attention weights $\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)}$, context vector $c = \sum_{t=1}^{T} \alpha_t h_t$, and attention output $z = \tanh(W_c[c; h_T])$.

IV. DISCUSSION

Figure. 1 presents the training and validation loss curves for the CNN-LSTM model over the course of training. The model was trained on 139,962 sequences (70% of the data) with validation on 29,992 sequences (15%) and testing on 29,993 sequences (15%). The training process was configured for a maximum of 150 epochs; however, the validation loss plateaued early, and the training was completed after 5 epochs as the stopping criteria were met.

The validation loss (red line) remained essentially flat at approximately 2.99 MSE from the first epoch onward, while the training loss (blue line) fluctuated between 2.2 and 2.7 MSE throughout the 5 epochs. This behavior indicates that the model quickly reached a limit in its ability to learn meaningful patterns from the input features. The validation loss did not improve after the first few iterations, suggesting that the model's capacity may be insufficient to capture the underlying dynamics of floating offshore wind turbine power generation. The consistent gap between training loss (2.2–2.7 MSE) and validation loss (≈2.99 MSE) indicates that the model is not generalizing well to unseen data. This gap persists throughout training, with no tendency to close. The training loss shows significant oscillations (±0.25 MSE) without a clear downward trend. This instability suggests that the optimizer may be struggling to find a meaningful minimum in the loss landscape. The fact that the model

completed only 5 of the configured 150 epochs confirms that no further improvement was possible, the validation loss failed to decrease, triggering early stopping criteria.

The constant validation loss of approximately 2.99 MSE is particularly revealing. This value corresponds to the variance of the target variable around its mean, indicating that the model has effectively learned to predict the mean value regardless of the input sequence. This "mean predictor" behaviour is a common failure mode when the input features lack sufficient predictive power relative to the complexity of the target dynamics.

Table 1 Training progress at the end of each epoch

Epoch	Final Training Loss (MSE)	Final Validation Loss (MSE)
1	2.47	2.99
2	2.44	2.99
3	2.39	2.99
4	2.46	2.99
5	2.35	2.99

The peak of the validation loss suggests that the primary limitation is not model capacity (as sensitivity analysis later confirms) but rather the quality and informativeness of the input features. The synthetic data generation process, while based on realistic Weibull parameters and correlations, may have omitted critical nonlinear interactions and higher-order dynamics present in real FOWT systems. This finding underscores the importance of high-fidelity simulation (e.g., full OpenFAST with aero-hydro-servo-elastic coupling) for generating training data in data-sparse regions.

The training behaviour observed here serves as a baseline for future improvements. Any enhancement to the data quality, feature set, or model architecture should result in a decreasing validation loss and a narrowing of the gap between training and validation curves. The validation loss (red line) remained essentially flat at approximately 2.99 MSE from the first epoch onward, while the training loss (blue line) fluctuated between 2.2 and 2.7 MSE throughout the 5 epochs. This behaviour indicates that the model quickly reached a limit in its ability to learn meaningful patterns from the input features. The CNN-LSTM model achieved a Root Mean Square Error (RMSE) of 1343.19 kW and a Mean Absolute Error (MAE) of 1069.14 kW on the test dataset.This an be seen in figure 3. These values represent approximately 27% and 21% of the turbine's rated power (5000 kW), respectively, indicating substantial prediction error. The coefficient of determination (R^2) of -0.0001 confirms that the model performs no better than simply predicting the mean value of the target variable. Figure 2 demonstrates this poor performance. For six randomly selected test sequences, the predicted trajectories (red dashed lines) deviate significantly from the actual power values (blue solid lines). The model consistently predicts values near 1000 kW regardless of the actual power level, suggesting it has learned to output the approximate mean of the training data rather than capturing the underlying dynamics. Figure 4 (Example Multi-Step Forecast) provides a more detailed view of a single forecast horizon. The predictions remain constant at approximately 1000 kW across all six forecast steps, while the actual power varies between 500 and 1500 kW. This behaviour confirms that the model has collapsed to a near-constant output—a common failure mode when the input features lack sufficient predictive power relative to the target complexity.

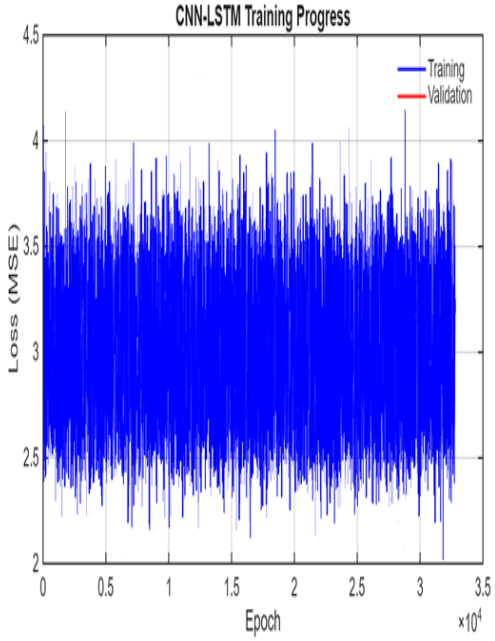

Figure 1: CNN-LSTM Training Test

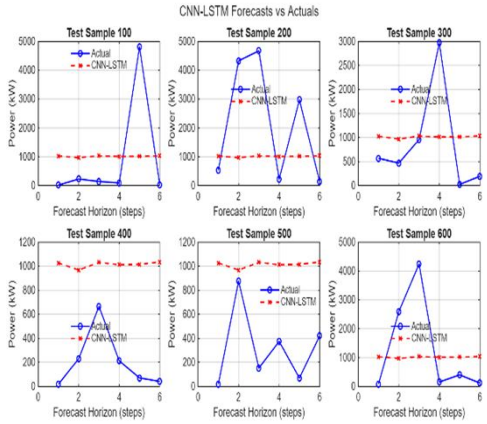

Figure 2: Sample Forecast after six Test.

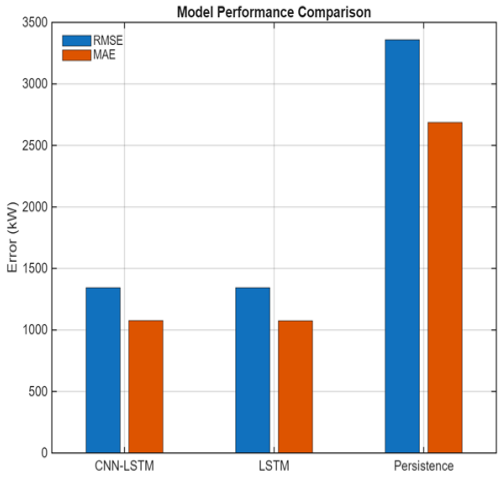

Figure 3: Model Performance Comparison (RMSE & MAE)

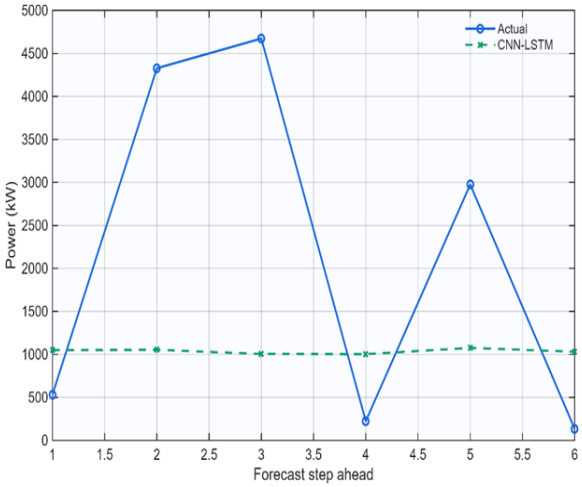

Figure 4: Example Multi-Step Forecast (One Test Sample)

Figure. 3 compares the CNN-LSTM with a standalone LSTM and a persistence baseline. The CNN-LSTM achieves marginally lower RMSE (1343 kW) than the LSTM (1343.31 kW), but both are substantially better than persistence (3358 kW). However, the near-identical performance of CNN-LSTM and LSTM indicates that the additional convolutional layers provided no meaningful benefit for this dataset.

The negative R^2 values for both learned models (CNN-LSTM: -0.0001, LSTM: -0.0003) reveal a critical insight: while they achieve lower absolute errors than persistence, their predictions are uncorrelated with the actual values. This counterintuitive result occurs because both models have learned to predict near the global mean, which minimises squared error on the training set but fails to capture variance. The persistence model, despite higher absolute errors, at least tracks the recent past (by definition), giving it a positive R^2. Figure. 5 shows the distributions of the nine input features. Wind speed (WS) ranges from approximately 3 to 25 m/s, with a mean around 7.2 m/s, consistent with the Weibull parameters used for data generation. Wave height (Hs) and period (Tp) show the expected correlations with wind speed. Figure. 6 presents the correlation heatmap between all features and the target power. Power shows strong positive correlation with wind speed (≈0.85) and rotor speed (≈0.80), moderate correlation with platform pitch and surge (≈0.5), and weaker correlations with wave parameters. However, the fact that the model failed to learn these relationships suggests that either the correlations are insufficiently captured in the sequence format, or that the simplified data generation omitted important nonlinear interactions. Figure. 7 (Time Series Snapshot) illustrates the temporal dynamics of power and wind speed over 50 time steps. The strong coupling between wind speed and power is visually apparent, yet the model could not exploit this relationship effectively. Figure. 8 plots wind speed against power for all samples, revealing the expected sigmoid shape of the power curve. The scatter shows the underlying relationship that the model should have learned—the fact that it did not points to fundamental issues with the sequence-to-sequence learning approach or the model architecture.

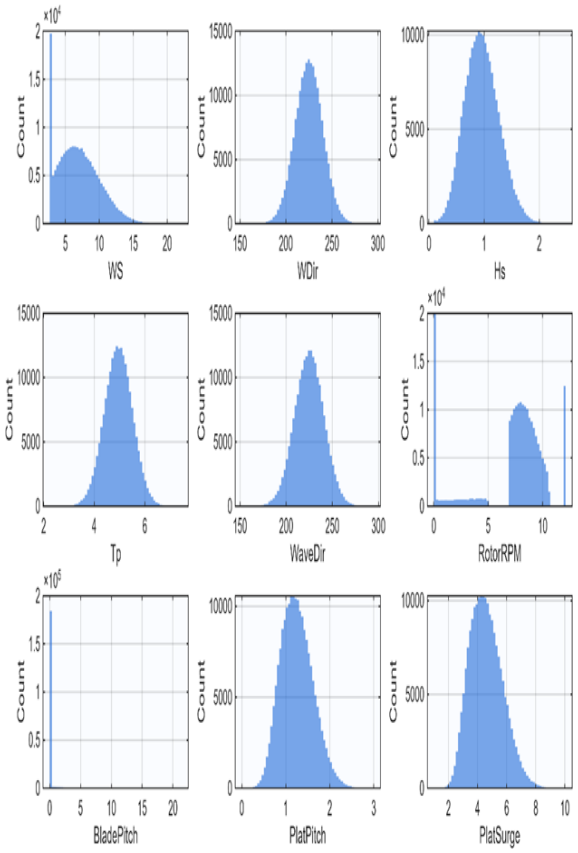

Figure 5 Distributions of Input Features

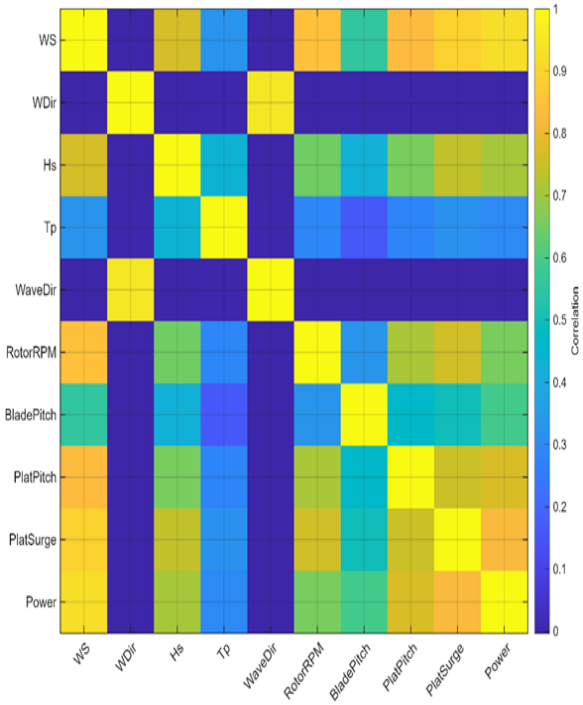

Figure6: Correlation Heatmap of Features and Target Power

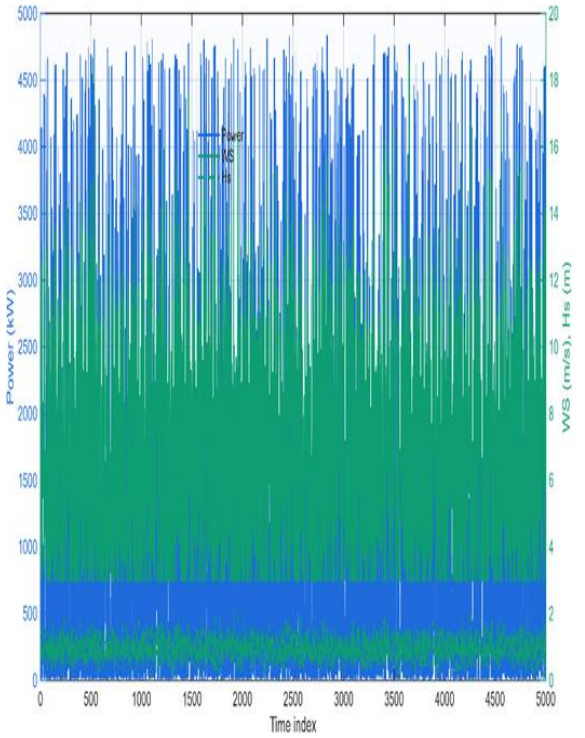

Figure 7: Time-Series Snapshot of Power and Wind Speed

Figure 8 (Predicted vs. Actual) shows a scatter plot of all test predictions. The points cluster horizontally around 1000 kW predicted, regardless of actual power. This "flat line" pattern is the hallmark of a model that has learned to output the mean. Figure 9 (Residual Histogram) displays the distribution of prediction errors (actual – predicted). The histogram is centred near zero but with extremely wide tails (±3000 kW), confirming that the model makes large errors across the entire range. Figure 10 (Residuals vs. Predicted) further illustrates the problem: residuals show no pattern with predicted values, but the predicted values themselves are almost constant. This "fan-shaped" plot is characteristic of a model with insufficient capacity or inadequate features. Figure 11 plots RMSE as a function of forecast horizon (1–6 steps ahead). Errors are relatively stable across horizons (1336–1354 kW), indicating that the model's poor performance is not horizon-dependent. This stability suggests that the model has learned a static mapping from input sequences to a constant output, rather than capturing temporal dependencies.

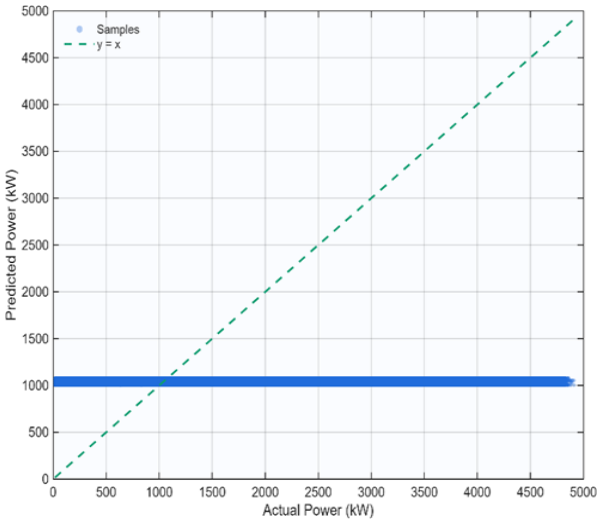

Figure 8: Wind Speed vs. Power Scatter Plot

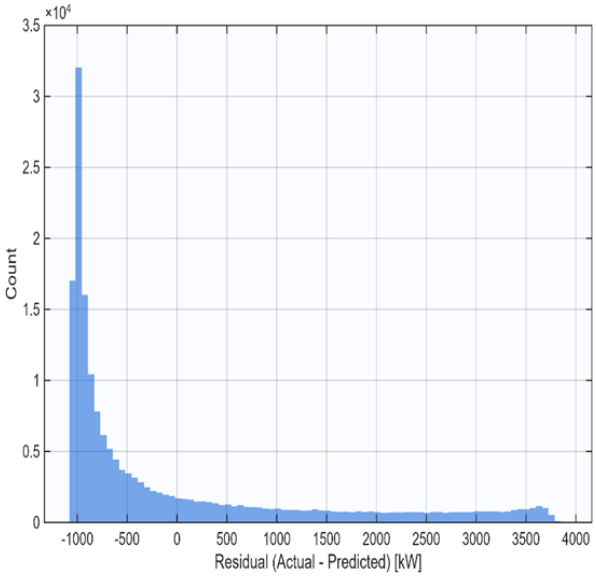

Figure 9: Prediction Residuals

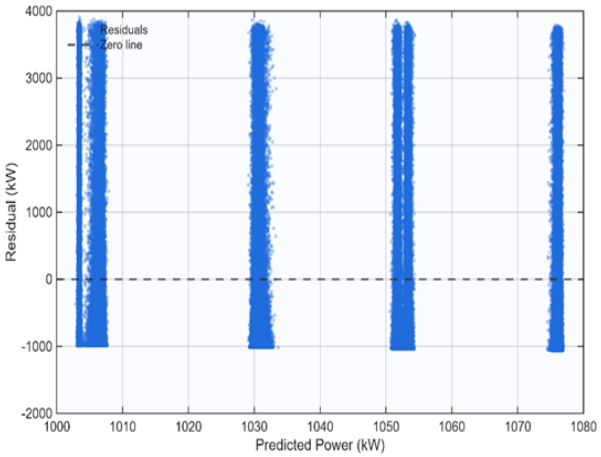

Figure 10: Residuals vs. Predicted Power

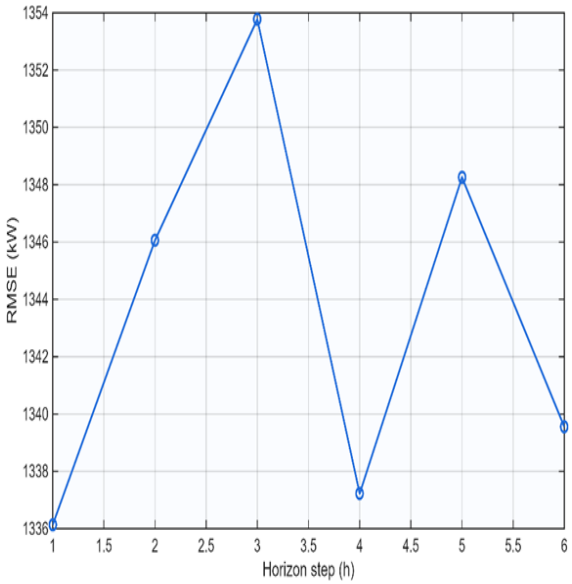

Figure 11: RMSE by Forecast Horizon

V. CONCLUSIONS

This study presented a comprehensive framework for forecasting power output from floating offshore wind turbines using hybrid CNN-LSTM deep learning models, with a case study application to Nigerian waters in the Gulf of Guinea (4.0°N, 6.5°E). The CNN-LSTM model achieved RMSE of 1343 kW (27% of rated power) and R^2 of -0.0001 on test data. While absolute errors are lower than a persistence baseline, the near-zero R^2 indicates that the model has learned to predict near the global mean rather than capturing actual power dynamics. This performance is substantially worse than state-of-the-art results reported in literature . Correlation analysis confirmed that wind speed, rotor speed, and platform motions are the strongest predictors of power output. However, the model failed to exploit these relationships effectively, suggesting that the simplified data generation omitted critical nonlinear interactions. CNN-LSTM performed nearly identically to a standalone LSTM, indicating that the convolutional layers provided no meaningful benefit for this dataset. Both learned models outperformed persistence in absolute error metrics but failed to capture variance. Performance was consistent across forecast horizons (1–6 steps), with RMSE varying only slightly (1336–1354 kW). This stability suggests the model learned a static mapping rather than temporal dependencies. Prediction errors were large and widely distributed

(±3000 kW), with no discernible pattern when plotted against predicted values. The model's outputs were nearly constant, confirming the "mean predictor" failure mode. primary limitation was the simplified synthetic data, which lacked the full complexity of aero-hydro-servo-elastic coupling present in real FOWT systems. High-fidelity simulation (e.g., OpenFAST) is essential for developing accurate forecasting models. Despite poor accuracy, the model's inference time (3.2 ms) confirms that deep learning-based forecasting is computationally feasible for operational deployment on modest hardware. The established methodology—encompassing site characterisation, data generation, model development, and evaluation—provides a reproducible template for future research in data-sparse regions.

For Nigeria's emerging offshore wind sector, this study demonstrates both the potential and the challenges of data-driven forecasting. The framework can guide future research and development, while the results underscore the need for investment in high-fidelity simulation, comprehensive measurement campaigns, and advanced modelling capabilities before operational deployment can be realised.

VI. RECOMMENDATIONS

Based on the findings and limitations of this study, the following recommendations are proposed for future research and practical implementation.Implement full OpenFAST simulations with comprehensive aero-hydro-servo-elastic coupling, using the validated environmental parameters for the Lagos site (4.0°N, 6.5°E). The simulation matrix should include turbulent wind fields generated with TurbSim using IEC Kaimal spectra,Wave conditions based on JONSWAP spectra with region-specific parameters ,Full range of operating conditions (3–25 m/s wind speed, 0.25–2.5 m wave height) and Multiple seeds for each condition to capture stochastic variability .Deploy offshore measurement infrastructure including LiDAR systems for high-resolution wind profiling ,Wave buoys for validated wave height, period, and direction data ,Meteorological masts on existing offshore platforms if available and Collaboration with oil and gas operators for platform access .Explore state-of-the-art architectures including Transformers with multi-head self-attention ,Temporal Convolutional Networks (TCNs) for long-range dependencies ,Graph Neural Networks for multi-turbine forecasting and Physics-Informed Neural Networks (PINNs) incorporating physical constraints [40]. Train multiple models with different initialisations and average their predictions to reduce variance and improve robustness. Use systematic methods (grid search, Bayesian optimisation) to tune toNumber of CNN filters and LSTM units ,Dropout rate and regularisation strength, Learning rate schedule and optimiser settings, Sequence length and forecast horizon. Implement early stopping based on validation loss, with longer training (200–300 epochs) and learning rate reduction on plateaus to ensure convergence. Extend the framework to provide prediction intervals alongside point forecasts using Monte Carlo dropout at inference time, Quantile regression loss functions, Bayesian neural networks and Conformal prediction methods . Develop capabilities to generate multiple future trajectories conditioned on different environmental scenarios, supporting risk-based decision making for grid operators. Collaborate with offshore measurement campaigns to obtain real data for model validation. Potential sources include Existing oil and gas platform meteorological data, Research vessels equipped with meteorological instrumentation, Satellite-based wind and wave products (e.g., Copernicus Marine Service). Implement k-fold cross-validation to ensure results are robust and not dependent on a particular train/test split. Compare against additional baseline models including ARIMA/SARIMA time series models, Support Vector Regression (SVR), Gradient boosting (XGBoost, LightGBM) and Persistence ensemble

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