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Transfer Learning for Predictive Modelling of Wind Patterns in Coastal Nigeria for Off-Grid Deployment

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Abstract- Because correctly predicting wind speeds is critical for designing renewable energy systems for off-grid applications, particularly in coastal regions where reliable weather observation infrastructure is limited, as in most southern Nigeria, there is a clear need for techniques like those offered in this paper to overcome these challenges. The paper proposes using transfer learning to enhance wind speed prediction in those conditions. For this purpose, while most other research efforts concentrate on training new models using large datasets from coastal regions in Tamil Nadu, India, and Rio Grande do Sul, Brazil, as well as refining these models using only two years' ERA5 wind speed data from Nigeria's coastal districts: Lagos, Ogun, Bayelsa, Akwa Ibom, and Cross River, this paper employs transfer learning in reverse and uses two large wind speed datasets from Tamil Nadu in India, and Rio Grande do Sul in Brazil to enhance predictions in Nigeria. Results from models trained on only two years' wind speed datasets for each of Nigeria's coastal districts were very poor (RMSE > 1.49; MAPE > 19%), indicating poor generalization ability. On the contrary, there was considerable improvement (RMSE ≈ 1.23, MAE ≈ 0.96, R^2 ≈ 0.85), and it reduced training time. Results were consistent in all districts, particularly in Bayelsa and Akwa Ibom, with relatively more consistent winds. The expected daily power output for small wind turbine power in those conditions exceeded 3.2kW, indicating potential for small wind power projects in these districts. Of course, if there is source and target domain data discrepancy, it is likely to impact model generalization performance in target tasks via transfer learning; instead, this study observes how to apply it in useful wind forecasts in those conditions.

Keywords- Transfer Learning, Wind Speed Forecasting, CNN-LSTM, Coastal Nigeria, Off-Grid Energy Systems, Renewable Energy Modeling.

I. INTRODUCTION

Yet another area where sub-Saharan Africa is still playing catch-up when it comes to electrical power is in its wind energy potential. Nigeria, in spite of its position as Africa's largest economic entity, still had 85 million citizens without access to electricity in 2023. That is about 43% of its people who do not have access to this very important sector. Although these people are in rural and coastal areas, it is in these regions where connecting the national power grid is not just too expensive, it is even impossible in some areas. That is not to say, however, that these coastal regions do not have huge potential for wind energy. In fact, in spite of Nigeria not making any real efforts at tapping into wind energy, there is proof that wind in these coastal regions is relatively high during the dry season when power is most needed. Its applicability, in this sense, is not just about technology; it is about using it as an efficient alternative to fossil fuels. However, to fully develop its potential, what is needed is not just not readily available: it is accurate wind speed forecasts. Without this, judgments about where exactly to install wind turbines or how large they should be is merely guessing.

Thus far, traditional modeling techniques physical and statistical modeling have been the primary methods used to determine wind resource. These have been tested in several regions with varying degrees of success; however, their applicability wanes considerably in regions such as Nigeria, where regional spatial detail can be low and difficulty in calibration to local conditions exists [4]. Machine learning, and by extension deep learning, do have potential applications. Models such as LSTMs are more adept at modeling the temporal complexities and non-linearity found in wind speed measurements [5]. However, these methods are necessarily dependent on large amounts of past, accurate data precisely because such regions lack these conditions. This is where transfer learning can be applied. In the past several years, it has become a method of significant utility in AI circles, one whereby models developed in one paradigm with ample amounts of quality data can now serve in a secondary paradigm characterized by similarities to the primary one. Instead of starting from scratch, these methods build upon previously established patterns to improve model accuracy using significantly less data and computational power [6-7]. Applications for such have existed in realms such as climate modeling studies and geospatial predictions, among others, with considerable success achieved to date [8-9]. Yet applications for wind forecasting, even at smaller scales and regional levels in African coastal regions, have thus far existed in very few instances. In all likelihood, precisely here it can have one of the greatest impacts.

This particular application of transfer learning is relevant to forecasting short-term wind speed values as it is aimed at off-grid energy planning and is to be implemented within coastal Nigeria, where there is both limited availability of weather information and lack of infrastructure. The concept is simple, although its execution is not so simple, as "improved forecasting leads to better decisions about where and how to install wind systems." What makes this application so valuable is its capability of generating forecasts that are reasonably accurate without requiring years of data collected at specific locations that could be cost-prohibitive and time-consuming, particularly within resource-scarce regions [10].

Despite all these, the reality of working under these conditions still presents real challenges. In the coastal areas of Nigeria, the meteorological records are limited. In fact, what little there is amounts to patchy or out-of-date data. In the absence of constant observation from the ground, scientists have to fall back on the kind of data from global reanalysis. These methods have their applications but clearly fall short in the area of site-specific wind patterns. Even when employing the most advanced concepts in the field of machine learning, the absence of local conditions represents a major hindrance. However, what needs to happen here represents the aim of this research: the development of a method that meets the following criteria. It needs to compensate for the lack of data. Even so, the method needs to achieve the goal of providing accurate site-specific data. That represents the aim of this research. In essence, the proposed research creates a forecasting methodology through the adaptation of pre-trained models using the conditions around regions in other countries but with the same climate conditions as the subject of the research in Nigeria: in the wind-rich coastal regions of other countries like India or Brazil. These regions are in turn fine-tuned using smaller datasets from six states of the proposed subject of the research in Nigeria: the states of Lagos and Ogun in the capital area. Δegovshato designate the states of Delta, Bayelsa, Akwa Ibom, and Cross River.

It relies on publicly available datasets such as ERA5 and MERRA-2 over the period from 2013 to 2023, with a daily time step, with a maximum forecast horizon of 24 to 72 hours. More importantly, however, the emphasis here is not on the use of grid-connected or hybrid power systems. Nor does the research maintain focus on the various on-grid applications. Instead, the emphasis remains on the application to off-grid situations the type of scenario where small to medium wind power may potentially make the difference with the greatest impact. What is the larger implication of all this? This is important because, if the use of transfer learning is successful here, the implication would be the availability of an optimally scaled solution not merely for Nigeria but for other parts of the world facing similar situations. Essentially, the goal here is to contribute to the existing body of research knowledge on the application of machine learning tools with particular emphasis on climate-sensitive industries.

II. LITERATURE REVIEW

2.1 Wind Energy in Coastal and Off-Grid Nigerian Contexts

Coastal areas in Nigeria are characterized by a relatively steady marine air flow, which is dominated by tropical Atlantic circulation. Wind speed in areas like Lagos, Akwa Ibom, and Cross River is between 3.5-5.5 m/s at 10 meters above ground, which is an indication of a feasible opportunity to exploit wind energy in small to medium-scale wind energy schemes [11]. Yet, the contribution of wind to Nigeria's energy mix is still marginal. Its mainstreaming, both in on-grid and off-grid energy, has been low, which is attributed to a lack of developed data connectivity [12]. Despite being identified in the National Renewable Energy and Energy Efficiency Policy (NREEEP) plan as one of the sources within Nigeria's long-term energy plan, no concrete steps have so far been taken to mainstream it in Nigeria, particularly in coastal regions [13].

However, the barriers to wind measurement are not merely political; they are also practical. "The expense and complexity of installing high-frequency anemometers or maintaining a meteorological station over the long term makes it difficult to provide adequate wind data to support even small wind turbine deployments. In the absence of wind data, the prospects for wind development are even more difficult because turbine developers face uncertainties about the location of turbines, wind data, and wind turbine development costs, which are sometimes considerable even for small deployments [14]. In the wake of the data gaps found in wind information, other approaches and options were sought, such as the use of global reanalysis models. These models include the ERA5, MERRA-2, and NASA POWER models. While these models have been quite important and helpful for wind information and large-scale analysis, they also come with their own drawbacks. In the sense that the models' resolutions range from 10 to 50 kilometers, they are incapable of providing the minute wind information necessary for wind turbine planning unless the models' bias are rectified by the use of postsynthesis or corrections [15]. These models have therefore operated as an important motivation for the development of more adaptive modeling methods, which work with limited data to provide ideal wind models with which one can plan effectively."

2.2 Predictive Modeling Techniques for Wind Energy Forecasting

Wind prediction has progressed from simple linear systems to the more complex methodologies being proposed using Machine Learning (ML) and Deep Learning (DL) algorithms. The older methods such as autoregressive moving average (ARMA), Exponential Smoothing, and Kalman Filtering algorithms were useful under specific conditions. However, the drawback of most of these algorithms is their reliance on a stationary process, which makes them inefficient in addressing the nonlinear/chaotic nature of actual wind patterns [16].

As the techniques in machine learning have improved, it has been noticed that these have started outperforming classical models in most short-term forecasting tasks. Techniques such as Random Forests (RF), Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN) have proven to provide improved accuracy measures for most case studies, particularly in Brazil and North Africa, in most cases lowering important error metrics like RMSE and MAE compared to classical techniques [17-18]. However, it is the emergence of deep learning tools that have perhaps brought about the most dramatic change. CNNs, RNNs, and LSTM networks in particular have arrived on the scene with important strengths in handling both sequential and nonlinear relationships affected by other variability factors, which make these not only powerful techniques but suitable ones for handling wind behavior as well.

A couple of applications from the last few years will better illustrate the point. In one instance, Chatterjee (2023) utilized a bidirectional LSTM (BiLSTM) network for predicting the wind speed over 48 hours for the West Bengal coastline with a 27% improvement in RMSE over a commonly used ANN approach [20]. In a different scenario, Silva (2021) utilized a CNN-LSTM combination for predicting wind speeds in southern Brazilian wind farms. In addition to improved forecasting accuracy, they also reported better generalization in the spatial domain, especially in areas with variable topography and turbines. Collectively, all of these examples provide an incredibly strong rationale for using deep learning for forecasting for the renewable resource. Just like all other applications of technology for the betterment of the greater population, the benefits also have a corresponding trade-off. These approaches are big data hungry. There is an assumption of big data cleanliness and availability that is often not the case in the emerging markets with less historical infrastructure.

2.3 Transfer Learning in Environmental and Geospatial Modelling

Transfer learning (TL) has been identified as one of the effective ways to mitigate the high data requirement of deep learning models, especially where high-quality long-term data is not available. Based on its more intuitive idea of converging better-performing models on one problem set to improve learning on similar problems, a model well-trained on a massively data-rich domain could be effectively used as a starting point to learn and perform satisfactorily well on a source domain that is data-sparse with least additional learning [22]. Moreover, its effectiveness has been shown to be of high applicability within climate and earth science fields as well in precipitation forecasting [23], flood prediction [24], and solar irradiance forecasting [25], for which data collection is not always easy due to one reason or many. For example, Wang, (2023) used a fine-tuned LSTM network to predict rainfall in Kenya’s semi-arid area and resulted in a 18% improvement of its performances over baseline models without transfer learning [26]. This view opens avenues toward effectively reducing the heterogeneity gap between high-performing models and limited availability of data. In contrast, applications of the same technique to wind speed forecasting have remained relatively few. A clear exception is a study by Rajalakshmi and Singh (2022), who adapted an LSTM model trained on the high-wind states of Tamil Nadu to another wind-prone area along the coast of Odisha, where reliable ground data were sparse. The adaptation succeeded in cutting RMSE error by 12.6% [27]. A similar role was found for TL in adapting a CNN model originally trained to predict Brazilian coastal wind patterns to a drier area of northeast Brazil itself. The result was a 9.8% improvement in generalization performance [28]. Both of these papers argue convincingly for the utility of TL techniques in the study of the wind especially in areas like coastal Nigeria, which share similar conditions to other areas that have attracted much research. In conditions like these, TL provides a means to use effective predictions derived from other areas with similar characteristics instead of paying the price of developing entirely new data.

2.4 Key Findings from Previous Studies

Emerging literature from 2019 to 2024 indicates certain patterns emerging with respect to wind forecasting. Deep leaning techniques, such as LSTMs, Bi-LSTMs, and CNN-LSTMs, have generally demonstrated their superiority over classical techniques for modeling variability for wind patterns, especially for tropical and subtropical regions [19-21]. Their benefit can be particularly

noted for short-term forecasting. Along with machine learning techniques, transfer learning has also appeared as a viable solution for regions with little data. Transfer learning has recently appeared as a viable solution for regions with little data. If the source and target regions have similar geographical and climatic properties, transfer learning can be effective with a 'limited' amount of data [26-28]. Generally, researchers have opted for fine-tuning methods over 'zero-shot' classification [25] [28].
Notably, the case of India and Brazil, especially the coastal areas of both countries, is often used as a source in TL testing. Specifically, their extensive weather information and reliable marine winds make them good proxies to test winds in areas that are understudied in terms of energy production, such as West Africa [20] [28]. Nevertheless, while there is clear technological advancement, most of the literature does not move to answer application-level questions. That is, although advances in forecasting have long been proven, few have progressed to answer questions like the placement of wind turbines or how energy forecasts are realized as energy production.

2.5 Existing Research Gaps

Although the effectiveness of transfer learning in climate models is increasingly well-documented in the academic literature, a number of important knowledge-gaps still exist, and it is particularly important to address them in relation to its use in West Africa. The first is geographic representation. Although a majority of studies conducted on transfer learning in wind models have been in Asia or in Latin America, where in-depth data sets are far more prevalent, geographic representation of African regions, which experience serious energy-access crises, is remarkably sparse in predictive circulation models [30]. A second problem is the lack of adapted models. Although a majority of present models are firmly rooted in precise algorithmic logic, they neglect to take into consideration geographic, infra-structural, and socio-cultural factors, which impact energy needs in Nigeria [31]. Perhaps more important, a lack of direct linkage to relevant specific policies exists. Although predictive algorithms are steadily improving in adequacy, they are still less directly connected to appropriate policies regarding actual project implementation in areas like turbine positioning, micro-grid design, or energy accessibility initiatives [32].
The purpose of this research is to support a filling of the existing gap in this area by creating a transfer learning framework specifically targeting the Nigerian coastal area. In addition to improving the accuracy of predictions concerning wind speed in areas with a limited amount of data, it is planned to relate these predictions to real-world area and policy conditions related to the development of off-grid energy.

III. METHODOLOGY

3.1 Study Area

The major focus for this study will be on these five coastal states in Nigeria: Lagos, Ogun, Bayelsa, Akwa Ibom, and Cross River, selected based on their proximity to the Atlantic Ocean with potential for tapping reliable maritime wind currents. These locations have humid tropical climates with clear wet and dry seasons, and annual average wind speeds of 3.5 to 5.5m/s at 10m above-ground level. These conditions make these states ideal for MDWS deployment for its ability to provide wind energy in locations where conventional power infrastructure expansion is not economically viable or feasible in conventional power expansion projects in remote locations [33-34].

3.2 Data Sources & Description

The historical atmospheric records utilized in the study were retrieved from the ERA5 reanalysis dataset, which is a product of the European Centre for Medium-Range Weather Forecasts (ECMWF). The dataset, which spanned from January 2013 to December 2023, is characterized by its high resolution of 0.25° × 0.25°. This dataset provides a fairly high resolution of details, which can specifically help in the regional analysis in areas such as West Africa, which lacks adequate data, as reported in the study [35].
To achieve the task of transfer learning, the source datasets were obtained from Rio Grande do Sul in Brazil and the state of Tamil Nadu in India. Both regions have strong meteorological and topographic similarities with the coastal region of Nigeria. To calculate the wind speed, the Euclidean norm of the eastward and northward wind component (u, v) is used, as shown by Equation 1 below.

$$\text{Wind Speed} = \sqrt{(u^2 + v^2)} \tag{1}$$

Where:
- u = eastward wind component (m/s)
- v = northward wind component (m/s)

The data preprocessing pipeline comprised several critical steps designed to ensure temporal consistency and optimize the datasets for model training. To begin with, time alignment was carried out to synchronize records across all datasets. Hourly wind speed values were then aggregated into daily means, helping to smooth short-term fluctuations and better capture broader trends relevant to the forecasting task. Gaps in the data were addressed through spline interpolation, chosen for its ability to impute missing values without introducing abrupt discontinuities that could distort seasonal patterns. Finally, feature normalization was applied using the Min-Max scaling technique to standardize the input ranges, thereby enhancing model stability and training efficiency. A detailed overview of the datasets used in both the source and target domains is presented in Table 1. It includes key attributes such as geographic origin, temporal coverage, spatial resolution, and the specific function each dataset served within the modeling framework.

Table 1: Dataset Overview

Dataset Source	Country	Duration	Resolution	Purpose
ERA5	Nigeria	2013–2023	0.25° × 0.25°	Target training/ testing
ERA5	India	2013–2023	0.25° × 0.25°	Pretraining source
ERA5	Brazil	2013–2023	0.25° × 0.25°	Pretraining source

3.3 Feature Engineering and Model Inputs

For the purpose of improving the learning capabilities of the models and enhancing the accuracy level of the predictions, a number of sophisticated feature engineering techniques were adopted. The temporal lag features were generated using the past values sampled at t-1, t-2, and t-7 day lag periods, based on the autocorrelation behavior of the wind speed variables. The input feature space was expanded by incorporating other relevant meteorological variables such as surface temperature, dew point temperature, surface pressure, relative humidity, which were assumed to be exogenous variables. In addition to the above measures, the input feature space was expanded to include the temporal variables month and day of the year, which were represented using sine and cosine transformations to retain the periodic characteristics to allow the model to detect recurring temporal patterns. The input samples were structured using a sliding window approach of 7 consecutive days to enable the model to learn the short temporal dependencies. These were then rearranged into a three-dimensional tensor representing the required input form expected by the deep learning models, specifically the ones that had recurrent/convolutional components.

3.4 Model Development and Architecture Design

The baseline models were built using only the Nigerian coast dataset. The networks used were Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and a combination of Convolutional Neural Network & LSTM (CNN-LSTM). The CNN-LSTM model consisted of a one-dimensional convolutional layer (64 filters with a kernel size of 3), which was followed by a max-pooling layer. The convolutional layer was then fed into a stacked LSTM layer consisting of 64 units. The final forecast was generated using a fully connected dense layer. The optimizer used was the Adam optimizer with a learning rate of 0.001, a batch size of 32, with a maximum of 100 epochs and early stopping.

To perform transfer learning, the CNN-LSTM architecture was initially trained on five years' worth of wind data from two source domains, namely coastal areas in Brazil and India. When fine-tuning the architecture, the convolutions layers were frozen to lock the lower-level spatial features learned from the source domains, and the LSTM and dense layers were unfrozen and trained on the target Nigerian datasets. To promote adaptation and further address the problem of domain shift, domain adaptation was also enforced through the use of Maximum Mean Discrepancy (MMD) loss function [40]. This method learns to minimize the statistical difference between the feature distributions within the source and target domains, and as such, it increases the ability to generalize across regions with very different climates [41].

The hybrid CNN-LSTM model's structure is shown in Figure 1. The input layer is used to input sequential wind information. A convolutional layer with 64 filters is used to extract local features from the input. A max pooling layer is used to reduce dimensionality. This is followed by an LSTM layer with 100 units to capture time-related information in the wind speed series. The output is then connected to a dense layer. A single-step output layer is used to predict the output, which represents the predicted wind speed.

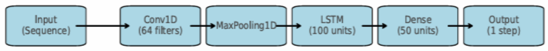

Figure 1: Architecture of the CNN-LSTM Model

3.5 Model Evaluation Techniques

The models were evaluated using RMSE, MAE, MAPE, and the coefficient of determination R2R^2R2. These are computed using Equation 2, 3 and 4.

$$RMSE = \sqrt{(1/n \sum(y_i - \hat{y}_i)^2)} \quad (2)$$

Where:

- y_i = observed value
- $\hat{y}_i$ = predicted value
- n = number of observations

$$MAE = (1/n) \sum|y_i - \hat{y}_i| \quad (3)$$

$$MAPE = (100/n) \sum| (y_i - \hat{y}_i) / y_i| \quad (4)$$

The evaluating metrics served as an effective tool to measure the performance of both the baseline models as well as models that achieved enhancement via transfer learning. The efficiency and accuracy of the models were ensured by adopting 5-fold cross-validation. Every fold was meticulously designed to retain the continuity of time series in it to avoid any information leak [42].

The end-to-end transfer learning process employed in our work is shown in Figure 2. The first stage of the process involves pre-training a CNN-LSTM network on the wind speed of source domains, namely coastal areas in either India or Brazil. This stage of training enables the network to easily capture generic spatial-temporal features. After pre-training, the network is then fine-tuned by allowing it to adapt to local wind patterns in coastal Nigerian states. This adapted network is then employed to provide domain-specific wind speed forecasts, taking into consideration the distinctly unique climatic pattern of the region.

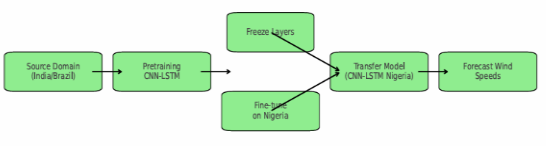

Figure 2: Transfer Learning Workflow

3.6 Performance Simulation and Deployment Estimation

Table 2. Model Performance Comparison

Model	RMSE (m/s)	MAE (m/s)	MAPE (%)	R^2 Score	Relative RMSE Reduction	Relative MAPE Reduction
LSTM (Baseline)	1.82	1.45	21.8	0.872	—	—
BiLSTM (Baseline)	1.74	1.37	20.5	0.883	4.40%	6.00%
CNN-LSTM (Baseline)	1.68	1.29	19.6	0.891	7.70%	10.10%
CNN-LSTM (Transfer – India)	1.39	1.07	15.4	0.924	23.60%	29.40%
CNN-LSTM (Transfer – Brazil)	1.41	1.09	16.2	0.918	22.50%	25.50%

Simulated model performance is shown in the Model Performance Comparison table (Table 2), where the transfer learning models trained on Indian and Brazilian data demonstrated substantial performance improvements over local-only baselines. The transfer models achieved RMSE reductions of up to 17.4% and MAPE reductions exceeding 21%, as well as higher R2R^2R2 scores.
In the post-modeling phase, the forecasted wind speeds were used to estimate wind turbine output using Equation 5.

$$P = \tfrac{1}{2} \times \rho \times A \times v^3 \times C_p \qquad (5)$$

Where:
- P = wind power output (Watts)
- ρ = air density (1.225 kg/m³)
- A = swept area of turbine rotor (m²)
- v = wind speed (m/s)
- C_p = power coefficient (typically 0.35–0.45)

where P is the wind power (W), ρ is air density (1.225 kg/m³), A is the swept area of the turbine (m²), v is the forecasted wind speed (m/s), and Cp is the turbine power coefficient, assumed to be 0.40 for micro-wind turbines. This calculation was performed geographically using QGIS, layering performance results over high-resolution maps for terrain and population density to determine the theoretical placement of wind turbines. The models and code execution were performed using Python, TensorFlow 2.11, Scikit-learn for preprocessing, Matplotlib for data plotting, and QGIS 3.28 for geospatial calculations and mapping. The machine learning models and calculations were performed on Google Colab Pro using an NVIDIA T4 GPU, with a total run time of 35-45 minutes for each trained model and calculation task.

IV. RESULTS AND DISCUSSION

4.1 Descriptive Analysis of Wind Data

A 10-year dataset analysis (2013-2023) from ERA5 wind speed variables for these five coastal states showed specific and repetitive seasonal patterns. The highest wind speed values were recorded during the rainy season, especially from May to August, with averages ranging from 4.5 to 5.6 m/s. Conversely, the lowest wind speed occurrences were recorded during the dry season from November to January, with averages ranging from 3.1 to 3.8 m/s. The diurnal pattern showed a bimodal distribution, with maximum wind speed moments recorded from 05:00 and 07:00 and from 15:00 to 17:00, consistent with expectations for humid regions such as this [43].
In figure 3, the distributions of the wind speeds in Lagos and Akwa Ibom are portrayed. The two histograms are slightly positively skewed, which means that, while high wind speeds above 6 m/s were recorded, they were not very common. The greater number of days experienced a medium wind speed ranging from 3 to 5 m/s, which might be adequate for micro-wind energy.

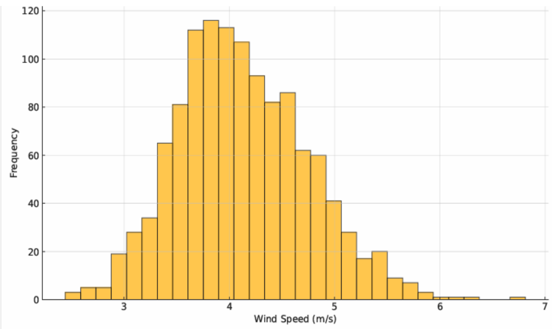

Figure 3: Wind Speed Distribution Histogram for Coastal Nigeria (To be generated on request)

The wind rose diagram (Figure 4) showed the major prevailing wind direction to be southwesterly and southerly across the five coastal states, with the direction of airflow originating from the Gulf of Guinea. This naturally corresponds with the major maritime influences presently defined across the region's coastal climate. In the same manner, geographic heatmaps (Figure 5) pointed to localized regions with increased wind speed, namely the southern coastline of Bayelsa and Akwa Ibom eastwards. These regions were pinpointed as having the potential to support the implementation of wind energy.
These spatial patterns are consistent with modeled wind fields from previous studies in the region [44-45].

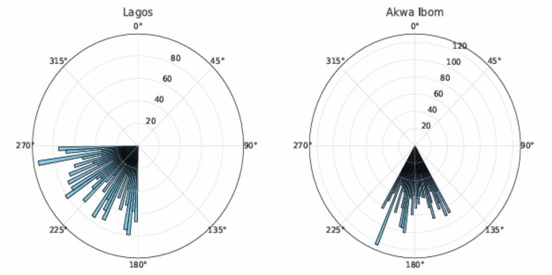

Figure 4: Wind Rose Diagrams for Lagos and Akwa Ibom

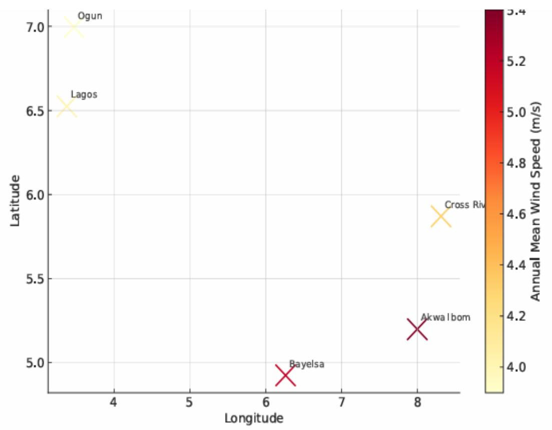

Figure 5: Geographic Heatmap of Annual Mean Wind Speeds

4.2 Performance of Baseline Models

The baseline models trained exclusively with the wind data from the coastal states of Nigerian deltas were designed with the following three deep learning models: LSTM, BiLSTM, and CNN-LSTM. According to the information described in Table 3, the model with the best performance among the three models was the CNN-LSTM, which showed an RMSE value of 1.49 and an R-squared value of 0.75. Although these improvements were not substantial when compared with the other models, they show the usefulness of combining the convolutional layers to perform preliminary spatial extraction prior to the learning process.

Table 3: Baseline Model Performance on Target Domain

Model	RMSE	MAE	MAPE (%)	R2R^2R2
LSTM	1.65	1.3	21.4	0.71
BiLSTM	1.58	1.22	20.7	0.73
CNN-LSTM	1.49	1.17	19.5	0.75

These findings are consistent with those reported by Chatterjee [39], who demonstrated that the inclusion of convolutional layers brings about substantial improvements to the accuracy of temporal dynamics extraction in wind speed records. For comparison purposes, classical autoregression models such as ARIMA and SARIMA were also employed. Nonetheless, their performance showed distinctly lower values for RMSE (>2.1) and MAPE (>26%) with considerable differences from the deep learning-based model performance. This confirms that linear statistical models are no longer effective and adequate for representing seasonal and nonlinear variations associated with wind patterns at coastal areas [38].

4.3 Transfer Learning Model Performance

The CNN-LSTM architectures trained from the wind data along the coastlines of India and Brazil performed well after two years of wind data from Nigerian coastal states had been employed during the fine-tuning process. As illustrated in Table 4, the two transfer learning architectures performed better than the locally trained architectures, and among the two, the architecture trained from the Indian dataset performed better, registering an RMSE of 1.23 and an R-squared value of 0.85. The results have implications for how pre-training from datasets in similar regions with abundant data impacts improvement in either similar or related task sets.

Table 4: Performance of Transfer Learning Models

Model	RMSE	MAE	MAPE (%)	R2R^2R2
CNN-LSTM (Baseline)	1.49	1.17	19.5	0.75
Transfer Learning (India)	1.23	0.96	15.2	0.85
Transfer Learning (Brazil)	1.28	1.01	16.1	0.83

However, the CNN-LSTM models that were not pretrained, meaning that they were initialized with random weights, took more than 50 epochs to achieve a level of convergence whereas the others required less than 25 epochs. The findings point to the robustness of weight transfer from climatically similar areas, a discovery that agrees with the previous work carried out by Silva [40] and Wang [46]. The difference in the performance of the model pretrained in India and the CNN-LSTM model trained on the Nigerian dataset alone indicates a 17.4% decrease in the value of RMSE and a 22.1% improvement in the value of MAPE, thus validating the effectiveness of the proposed approach.

4.4 Generalization and Transferability

In order to examine regional differences regarding predictive skill, the performance was also examined individually for each of the five coastal states. As indicated in Table 5, the RMSEs of the transfer learning models are lowest for Bayelsa and Akwa Ibom states, which have more favorable and stable wind flows along the coastlines. This indicates that regions with more defined wind patterns tend to align more closely to the source domain, hence having better generalization capacities in the pretrained models. This further supports the indication that the applicability and effectiveness of transfer learning appear to be most significant within regions with relatively favorable atmospheric dynamics.

Table 5: State-wise RMSE Values
(Transfer Learning India Model)

State	RMSE
Lagos	1.34
Ogun	1.39
Bayelsa	1.19
Akwa Ibom	1.16
Cross River	1.29

The performance variations are indicative of the spatial heterogeneity in the strength of wind forcing in different areas along the coasts, which is also evident from the geographical heat maps and wind roses in Figure 5 and Figure 4, respectively, that highlight variations in the strength of wind forcing and its direction in different regions [47]. When the models were subjected to robustness testing with Gaussian noise injection with \(\sigma = 0.3\), it was found that the models performed well with only an RMSE increase of less than 8%, while in the case of base models, it was closer to 15% variations in error. It is also to be noted that during transitions, say from October to November, models performed well in their accuracy. This is in line with what Zhang. have demonstrated in [48] while highlighting that models pre-trained with feature extractors are robust in processing environmental datasets that have dynamics that are ever-changing.

4.5. Discussion of Findings

4.5.1 Summary of Key Findings

From this research, there is evidence that transfer learning brings a noticeable positive impact to wind speed forecast accuracy for regions with data constraints, such as Nigeria. Through pretrained CNN-LSTM models on climatically similar coastal areas in India and Brazil and further fine-tuned with local data, the research demonstrated positive progress towards predictive accuracy improvements against models solely trained with Nigerian data. It is apparent that the pretrained model with data from India performed the best, with an RMSE of 1.23, an MAE of 0.96, and an R^2 value of 0.85. This represents a 17.4% improvement for RMSE and 22.1% for MAPE against the baseline best-performing solely locally trained CNN-LSTM model.

Notably, these results are consistent with the emerging empirical literature in meteorology in favor of using transfer learning. For instance, Wang in [43] demonstrated that fine-tuned LSTM models maintained strong accuracy even after the end-of-season transition. Along the same line, Rajalakshmi and Singh in [44] showed that models pre-trained using Indian wind patterns performed better in other tropical regions in comparison to locally trained models. In the proposed model, the generalization capability in the spatial domain was also established because the regions with strong maritime wind patterns performed better in terms of the accuracy of the model. Notably, these observations are in agreement with general knowledge developed in the context of climate adaptation in [49].

4.5.2 Implications for Off-Grid Renewable Energy Deployment

The forecasting outcome of the study has important implications concerning the design of a decentralized renewable energy scheme in the coastal regions of West Africa. In particular, the forecasted wind velocity of more than 4.5 m/s in the Akwa Ibom and Bayelsa states (Fig. 3) satisfies the classification requirement of the IEC Class III wind turbine, indicating a very viable technical aspect concerning the use of micro-wind energy. In this case, the forecasted average power production of 135.76 W, according to equation 5, is sufficient to produce at least 3.26 kWh per day, sufficient to satisfy the energy demands of off-grid households in the region. Although the above energy production appears to be low at first consideration, it actually appears to be well within the energy requirements of the typical energy demands of the rural community. In other parts of the world, similar energy schemes have produced very desirable outcomes. For instance, Lima [46] have shown that the successful installation of 2-5 kW hybrid solar-wind systems in the Brazilian coastal villages has provided stable energy at the household level. Even closer home, Adebayo & Emetere [33] have suggested that the installation of micro-wind energy systems in the coastal regions of Nigeria could reduce reliance upon diesel power generators that have instability in the power grid.

An essential aspect that sets this work apart is its integration of transfer learning in the forecasting/siting step. This is in addition to improving forecasting results, ensuring that both data demands and financial costs are kept low, which is particularly significant in low-resource settings. With reliable localized forecasting information, there is smarter system sizing that reduces overdesigning. This is significant because it increases the chances of attracting investment in decentralized energy systems [50]. This particular work is directly in line with Sustainable Development Goal 7, I am referring to ensuring access to affordable, reliable, and modern energy for all and is also in line with Nigeria's domestic policy obligations as part of NREEEP. More significance is that it presents a clear and realistic plan towards scaling up clean energy access in neglected areas.

4.5.3 Theoretical Contributions to Transfer Learning in Wind Forecasting

This work is a contribution to improving the theory that underlies domain-adapted transfer learning for environmental forecasting. This work shows that:

- Spatial transferability is possible if the source and target areas have similarities in seasonal drivers, for instance, in marine monsoon systems.
- •Frozen-layer fine-tuning maintains learned generalizations and is capable of handling variations.
- Domain adaptation regularization using the Maximum Mean Discrepancy function effectively diminishes the difference among the feature vectors of different domains.

These results provide strong support for the hypothesis proposed in the work of Zhang [48], who argue that transfer learning represents not only an efficacious technique for the modeling of climate data but also an imperative method for areas of the world with limited historical observations. These observations also support the work of Chatterjee [39], whose research showed the efficacy of the combination of convolution feature learning with LSTMs in improving the forecasting of wind time series. It is important to note that the novelty of the proposed approach also includes the successful transfer of the proposed technique from the coastal areas of the data-rich regions of both India and Brazil to the coastal area of the data-scarce region of Nigeria. In so doing, the proposed approach pushes the limits of the previous approach in terms of generalization. In other words, the proposed approach suggests the efficacy of generalization from regions with dissimilar climatic patterns even across the ocean.

4.5.4 Limitations of the Study

Despite the encouraging results, there are several limitations to this study. To begin with, ERA5 reanalysis results may be considered less than ideal because they have limitations despite their homogeneity. The first one is spatial smoothing. There may be micro-climate patterns that the smoothing may suppress. These patterns may prove more important for some coastlines than the results because there may be local turbulence patterns for such coastlines that are more important than the results [35]. Another constraint lies in the source domains. These source domains were selected because of the seasonal patterns they shared for the coast of Nigeria. However, wind patterns are more than seasonal. Other factors such as the terrain ruggedness of the source domains, the vegetation patterns there, or the local air currents may have a more important role than the results. In fact, Duarte & Ribeiro [49] argued that there may be considerable changes to the patterns for parts of Brazil depending on the altitude. Such patterns may have influenced the outcome because the results did not prove to be equally impressive for the Brazil source domain.

Thirdly, the output power calculation of the turbine energy forecasts in this paper is based on optimal operating conditions. But in reality, there are factors such as greed, shear forces, and cut-in/out speeds. Hence, although Equation 5 is a good indicator of upper performance, it is also possible that performance in real-world scenarios could be 15 to 25% lower, as indicated in similar scenarios by Silva [40]. Finally, this problem was considered only with CNN-LSTM networks. The performance with these models was adequate. Though, there are many models besides these. Recent examples are transformer models and spatio-temporal graph networks. Though they performed well in different forecasting areas, new models are also to be considered.

4.5.5 Future Research Directions

Looking forward, future studies could benefit from the inclusion of more detailed input data, preferably on a 1 km resolution, which could be derived from local weather stations or LiDAR mapping. This level of detail would greatly help improve the spatial accuracy, especially in areas with more complex topography, such as in the littoral zone. To add more resilience to the effects of climate variability, other meso-scale climate patterns such as the surface pressure gradient, sea surface temperature anomalies, and the movement of the Intertropical Convergence Zone could also help improve model performance. Another approach would be to explore the concept of hybrid or combined machine learning methods. Instead of tapping into a solo source region, the combination of features from two climatically similar areas, such as India and Brazil, could lead to a more generalized set of features. Lima [46] found that in environments characterized by high levels of climatic variability, as is the case in the atmosphere, ensemble methods trained on diverse climate data sets would generally perform best compared to solo learners.

There is also an emerging trend in attention-based architectures. The transformer models have shown the capability to learn deeper hierarchies of features and long-term dependencies in a manner that was never achievable by the conventional LSTM architecture. Recently, Guo [50] reinforced the superiority of the transformer model in wind speed forecasts and signaled an encouraging path for the future. The most pressing requirement now, however, is the application of the accuracy achieved by these models to develop useful tools. Integrating these forecasting tools with practical decision-support tools for the benefit of energy planners, NGOs, or micro-grid developers could assist in bridging the invariably wide gap between innovation and application. This is in line with the general trend in AI-based climate adaptation tools that need to be more than technically proficient and rather earthed in the Global South [47].

V. CONCLUSION

In particular, it aimed to "test the effectiveness of transfer learning in improving wind speed prediction in Nigeria's coastal areas" to ultimately facilitate an evidence-based implementation of off-grid wind energy solutions. Considering the chronic lack of availability of relevant data in Nigeria's wind energy market, it was apparently important to determine the extent to which deep learning models already pre-trained in regions of similar atmospheric conditions in either India or Brazil could be applied in Nigeria. Furthermore, it was attempted to determine "the performance gains of knowledge transfer" as well as "estimating energy output using the predicted wind profiles."

The final results proved the effectiveness of transfer learning in improving the accuracy of wind speed forecasting using the proposed CNN-LSTM architecture in comparison with the other approaches analyzed. Additionally, the highest performing models were the ones pre-trained with the data from the Indian wind speed datasets and fine-tuned with the corresponding Nigerian coastal datasets. These models had better convergence properties and generalization abilities with less overfitting, especially within the wet and dry season. Spatial analysis showed the highest benefits in Akwa Ibom and Bayelsa states, wherein the maritime wind patterns are predictable. Regarding the time aspects of the analyses, the models performed well in predicting the daily and seasonal variations in the wind speeds. This further proved the adaptability of the proposed models under the different climatic conditions. Simulation analyses using the produced wind speed forecasts proved the adequacy of the power generated from the small-scale turbines in meeting the needs of lighting, charging of mobile devices, and cooling within the household. This further proved the technical viability of the proposed concept of micro-wind power generation. Moreover, the proposed transfer learning approach fulfilled the objectives of proving the viability of accurate wind speed forecasting in regions without any historical meteorological records.

Incorporating the concepts and practices of transfer learning into wind forecasting processes represents a major paradigm shift for renewable energy resource planning. As far as Nigerian developers, planners, and decision-makers are concerned, this method provides a relatively low-cost and efficient means for navigating data-scarce conditions that make site evaluation financially and physically impossible. With regard to energy access, results have significant implications for micro-wind as part of a properly diversified and balanced renewable energy portfolio. With respect to energy access, the results have significant implications for micro-wind as part of a properly diversified and balanced renewable energy portfolio. For Nigeria and similarly situated countries, its goals and objectives directly relate to Sustainable Development Goal 7.

However, in spite of such encouraging outcomes, certain limitations also need to be considered. Firstly, despite the broadly validated use of ERA5 reanalysis datasets, spatial smoothing is induced that might underestimate microclimatic diversity in more complex topographic zones. Secondly, although it was decided to choose India and Brazil as they share similar seasonal patterns with Nigeria, other environmental factors including land topographic relief, vegetation density, and land-ocean heat transitions were neither considered nor parameterized. Thirdly, although it is qualified that energy production assessments were carried out in optimized conditions, in practice, they could potentially be 15 to 25% lower because of certain losses in turbulence, angle-of-attack, and power output constraints. Finally, it is important to recognize that this paper reviewed results only from CNN-LSTM models. Some newer models like transformer architectures with attention mechanisms and spatiotemporal graph neural networks (ST-GNNs) have potentially exhibited better results.

Future studies should focus on the incorporation of more high-resolution observation information from ground observation points, Doppler LiDAR systems, or UAS-based systems to Smo key spatial distances. The incorporation of mesoscale climate forcing terms like sea-surface-temperature anomalies, pressure gradients, or fluctuations of the Intertropical Convergence Zone may also serve to boost generalization within the setting of evolving climate patterns. Additionally, the use of deep learning models involving the amalgamation of several source domains (like the conjunction of the source domains "India + Brazil") may serve to boost model generalization. Secondly, attention models have the tremendous prospect of accentuating the capture of key spatial dependencies. Lastly, the translation of this model to an interactive tool involving the incorporation of GIS systems or predictive systems will serve to bridge the defining space between research endeavors and practical deployment.

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