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Research Article

Investigation of Wind Speed to Generate Energy Using Machine Learning Algorithms Approach Over Selected Nigerian Stations

Francis Olatunbosun Aweda [a*], Segun Adebayo [b], Adetunji Ayokunnu Adeniji [a], Timothy Kayode Samson [c], Jacob Adebayo Akinpelu [a]

[a] *Physics Programme, College of Agriculture Engineering and Science, Bowen University, P.M.B. 284, Iwo, Nigeria.*
[b] *Mechatronics Engineering Programme, College of Agriculture Engineering and Science, Bowen University, P. M. B. 284, Iwo, Nigeria.*
[c] *Statistics Programme, College of Agriculture Engineering and Science, Bowen University, P. M. B. 284, Iwo, Nigeria.*

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A B S T R A C T

Wind energy has been identified as a critical component in the growth of all countries throughout the world. Nigeria has been identified as having energy issues as a result of poor maintenance of hydro and thermal energy generating stations. As a result, the current study uses some machine learning approaches over wind speed data for energy generation in the country. Machine learning models were employed for wind speed using selected meteorological parameters. Little research was done using some meteorological data and machine learning to investigate wind speed across Nigerian sub-stations, resulting in the need for further research. This research, on the other hand, focuses on a neural network for forecasting, a Long Short-Term Memory (LSTM) network model based on several fire-work algorithms (FWA). The data for this study came from the archive of the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) Web service, which was modeled. The LSTM predicts the wind speed model based on the FWA, which used hyper-parameter optimization and was based on a real-time prediction model that was dependent on the change and dependence of the neural network. The study data was split into two categories: test and training. According to the validation technique, the sample data was reviewed, and the first 80 % of the data was utilized for training, as revealed by the (LSTM) network model. The remaining 20 % of the data was used as forecast data to ensure that the model was accurate. The normalization of the data for the wind speed range of 0 to 1 which illustrates the process data, the high peak in 1985 (a = 0.12 m/s, b = 0.11 m/s, c = 0.13 m/s, d = 0.08 m/s, e = 0.06 m/s, f = 0.10 m/s) was discovered. However, the summary result of the performances of different 11 Machine Learning algorithms of regression type for each of the seven locations in Nigeria has different values. As a result, it is recommended that this study will facilitate the prediction of wind speed for energy generation in Nigeria.

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1. INTRODUCTION

Energy challenges have been an issue for decades around the world; however, wind energy is quickly gaining acceptance for the development of any country around the world through economic and commercial use for technological development. According to (Staff, 2012), a more equitable number of people have not benefitted from their national grid all over the world, particularly in the African sub-region. These challenges have grown fast in Nigeria due to the low supply of the national grid to its populace, thus attenuating the industrialization and development of the nation due to low or no power supply for the nation. Research has shown that wind energy has been known to be one of the major sources of energy (Dhunny et al., 2014; Pobočíková & Sedliačková, 2014; Salahaddin, 2013), which contributes to electricity production (Dhunny et al., 2014; Pobočíková & Sedliačková, 2014; Salahaddin, 2013) and has been considered by so many countries across the world (Dhunny et al., 2014; Pobočíková & Sedliačková, 2014; Salahaddin, 2013). However, (Pishgar-Komleh et al., 2015) reported that wind energy distribution was shown as a power generation, which contributed to Weibull distribution among other forms of energy generation. More so, (Agbo et al., 2021) reported that Nigeria's energy production could benefit from the use of wind energy. It was reported that, on average, wind energy velocity prediction contributed to the rotation of wind energy turbines in wind farms and, thus, this energy generation played a role in the development of any nation (Salahaddin, 2013). Authors in (Aliyu et al., 2015; Oyedepo, 2014) suggested methods for promoting the utilization of wind energy in Nigeria that are equally applicable to other sub-Sahara African countries; however, the major factors militating against the wind energy deployment

*Corresponding Author's Email: aweda.francis@bowen.edu.ng (F.O. Aweda)
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in most of these countries are lack of government clear policies on wind energy and the economy of technologies. Authors in (Asiegbu, 2007; Munteanu et al., 2008; Ohunakin & Akinnawonu, 2012) found that the estimation of wind energy helped form several methods (Asiegbu, 2007; Munteanu et al., 2008; Ohunakin & Akinnawonu, 2012) for the generation of wind energy. This also shows that the usage of statistical analysis (Asiegbu, 2007; Munteanu et al., 2008; Ohunakin & Akinnawonu, 2012) to describe wind energy (Asiegbu, 2007; Munteanu et al., 2008; Ohunakin & Akinnawonu, 2012) adds to some good research (Asiegbu, 2007; Munteanu et al., 2008; Ohunakin & Akinnawonu, 2012) about wind energy generation (Chang, 2011a, 2011b; Justus et al., 1978; Kaoga et al., 2014; Martin et al., 1999; Mert & Karakuş, 2015; Waewsak et al., 2011). However, the authors of this study prefer to investigate wind energy using a machine learning approach. There is universal agreement that reliable and environmentally acceptable energy sources are critical to meeting rising energy demand (Asiegbu, 2007; Munteanu et al., 2008; Ohunakin & Akinnawonu, 2012), which is increasing at a faster rate than previously (Asiegbu, 2007; Munteanu et al., 2008; Ohunakin & Akinnawonu, 2012), due to high population growth (Asiegbu, 2007; Munteanu et al., 2008; Ohunakin & Akinnawonu, 2012), technological advancements, and development, among other factors (Antor & Wollega, 2020; Oyewole et al., 2019). Airstream and lunar energy bases appear to be viable options for renewable energy sources (Antor & Wollega, 2020). On the other hand, predicting the output of renewable energy sources is extremely challenging (Antor & Wollega, 2020). Different authors have worked on wind; some of them uses Sentinel 1 satellite image analysis by SNAP software (Majidi Nezhad et al., 2022) to conduct wind source potential assessment; a new forecasting model is based on machine learning in Sardinia. However, the authors in (Neshat et al., 2022) used quaternion convolutional long short-term memory neural model and adaptive decomposition method for wind speed forecasting in the north Aegean islands. Moreover, in (Majidi Nezhad et al., 2022), researchers investigated the sites that prioritize offshore wind energy potential and mapping for installation of wind forms in an Iranian Island. Furthermore, this study (Majidi Nezhad et al., 2020; Majidi Nezhad et al., 2022) worked on Mediterranean Sea offshore wind classification using MERRA-2 and machine learning models. However, for this research, the author uses MERRA-2 data to investigate wind speed for energy generation using a machine learning algorithm approach over selected Nigerian stations. However, because of the scarcity of electricity in Nigeria, this study was conducted.

This research aims to investigate wind speed using a machine learning algorithm approach over selected Nigeria stations. However, Machine Learning (ML) algorithms require effective training and testing to make correct predictions. Many datasets are utilized for various purposes to develop an algorithm that will generate predictions and judgments based on data from the real world according to different authors, as shown in Table 1.

Table 1. The use of multi-criteria decision-making methods by multiple studies

Methods	Description	Location	References
CEEMDAN, VMD technique, and LSTM	Application of hybrid model	China	(Ma et al., 2020)
LSTM neural network and optimal input sets	wind speed forecasting	Iran	(Memarzadeh & Keynia, 2020)
Hybrid model and LSTM	Multi-step wind speed forecasting	Brazil	(Moreno et al., 2020)
Hybrid Laguerre neural network	Wind power forecasting	China	(Wang et al., 2020)
Machine learning in biomedical datasets	Training and testing process	Turkey	(Uçar et al., 2020)
ANN	Prediction of wind speed and wind direction	Brazil	(Khosravi et al., 2018)
Predictive model	Stepwise regression and grid search	Nigeria	(Olubi et al., 2021)
ANN	Wind power density forecasting	Spain	(Rodríguez et al., 2020)
ANN	Forecasting of wind power generation	Greece	(Zafirakis et al., 2019)
ANN	Wind speed distribution	Saudi Arabia	(Brahimi et al., 2019)
ANN	Wind speed prediction	India	(Navas et al., 2020)
Wind speed prediction model	Wind speed prediction	Nigeria	(Lawan et al., 2020)
high-frequency wind power prediction	Wind speed prediction	United Kingdom	(Lin et al., 2020)
ANN	Wind turbine power prediction	Sri Lanka	(Nielson et al., 2020)
Hybrid Approach	E-mail spam	Iran	(Hassani et al., 2020)
Hybrid renewable energy system	Renewable energy system	Chennai	(Venkatakrishnan et al., 2021)
LSTM prediction	Wind speed prediction	China	(Zhang et al., 2019)
Neural network approach	Wind speed forecasting	China	(Liu et al., 2020)
Wind turbine based	Control of pitch angle	Iran	(Hosseini et al., 2022)
A numerical analysis using WT	Wind turbine power regulation	United Kingdom	(Maheri et al., 2022)

2. Network architecture with long-short time memory (LSTM)

The LSTM layer captures the temporal dependence of prior wind speed on future wind speed (Zhang et al., 2019). The information of the nonlinear correlation has a linear and maximal correlation coefficient according to Pearson's correlation. The LSTM network reveals that in the nearby gate dataset, there is a need to compare the performance of huge datasets with previously published larger predictors.

According to many studies, the gate of the input dataset undergoes sigmoid variation, resulting in the tanh of the data function. This function displays the weight value that falls within the range of -1 to 1, as given in the formulae below:

$$i_t = \sigma(w_i[h_{(t-1)}, x_t] + b_i) \quad (1)$$

$$c_t = \tanh(w_c[h_{(t-1)}, x_t] + b_c) \quad (2)$$

$$f_t = \sigma(w_f[h_{(t-1)}, x_t] + b_f) \quad (3)$$

The examined state ($h_{(t-1)}$) has a significant value in the input ($x_{(t)}$) and the outnumber of the state cell ($c_{(t-1)}$) where the value is shown to be zero. The decided gate forgot using the sigmoid input function that varied from different networks, showing that the examined state ($c_{(t-1)}$) has a significant value in the input($x_{(t)}$) and the outnumber of the state cell ($c_{(t-1)}$). This value is occasionally left out of the actual value 1 that is retained. However, the architectural output that passed through the sigmoid function gate revealed a value of 0 to 1 (Asiegbu, 2007; Munteanu et al., 2008; Ohunakin & Akinnawonu, 2012). However, the function tanh returns the weight reflection level of the output sigmoid function's crucial multiple (Adebayo et al., 2013; Shao et al., 2021).

$$o_{(t)} = \sigma(w_o[h_{(t-1)}, x_t] + b_o) \quad (4)$$

$$h_{(t)} = o_{(t)} \times \tanh(c_t) \quad (5)$$

2.1. Network of Recurrent Neural Networks (RNN)

The feed-forward network displays information from the forward direction with the input node, which could be a ring or a sequence network (Shao et al., 2021; Yin et al., 2017). There have been some decisions that have been made based on the predictions of some future events that are relevant to the current input. The feed-forward network is a severe problem to deal with since it resulted in a succession of data with no memory timeline. The recurrent neural network illustrates that the feed-forward network allows for the aforementioned output, which is based on the data input. The internal state memory of the recurrent neural network displays a sequence of input datasets. This network shows that the architectural design and application of the neural network have a significant impact on the processing of some learning languages in machines (Yin et al., 2017). This network can be mathematically represented as follows:

$$h_{(t)} = f_c(h_{(t-1)}, x_{(t)}) \quad (6)$$

where f_c is the parameterized function, $h_{(t-1)}$, $x_{(t)}$ is the input vector at time step t and is the previous state. When you use the activation function, you get:

$$h_{(t)} = \tanh(w_{hh} h_{(t-1)} + w_{xh} x_{(t)}) \quad (7)$$

and the output state is described as follows:

$$y_{(y)} = w_{hy} h_{(t)} \quad (8)$$

W indicates that the hidden vector for a unit neuron is the input weight, h. The prior weight is known as w_{hh}, whereas the present weight is known as w_{xh}. The Recurrent Neural Network (RNN) is stated to be divided into several categories. Multiple single output data (MISOD), multiple outputs, multiple inputs data (MOMID), single input, single, single output data (SISOD), and single input, multiple outputs data (SIMOD) are among these classes; however, the RNN, which is heavily influenced by some of the affected gradients, vanishes as a result of the significant problem encountered.

The Fireworks Algorithm (FWA) (Tan & Zhu, 2010) is a swarm intelligence algorithm that selects a set of random points constrained by some distance metrics in the hope that one or more of them will produce promising results (Zheng et al., 2013), allowing for a more focused search and, thereby, exploring a very large solution space in this way. The algorithm (Zheng et al., 2013) demonstrated that promising result (Salahaddin, 2013) in solutions to complex problem (Li & Tan, 2019) in a large data space (Zhang et al., 2015).

Furthermore, FWA was combined (Aliyu et al., 2015) with LSTM to improve the performance of the time series model of weather data (Pei et al., 2012).

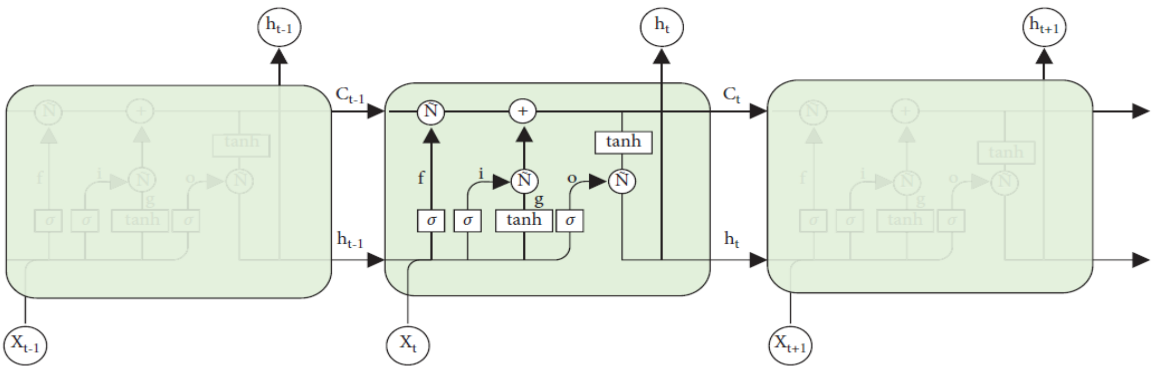


Figure 1. The LSTM's fundamental principle

3. EXPERIMENTAL

3.1. Model used for the research

For this research, the model used is based on the Artificial Neural Network and 11 different machine learning methods employed in this study; however, the data was submitted to different percentages: for example, 80 % of the data was trained while 20 % of the data was tested using Artificial Neural Network (ANN). The accuracy of machine learning algorithms in predicting wind speed in seven Nigerian cities (Sokoto, Maiduguri, Ilorin, Ikeja, Port Harcourt, and Abuja) is compared in this study, but it has a direct impact on wind generation at each location. For testing the algorithms, data samples of over 324,120 hours with 20 predictors (i.e. factors) for the wind speed response variables were obtained from the Solar Data Analysis (SoDa) website archive. The research data is derived from meteorological database parameters. Clustering data were employed to examine the dataset to get insight into it and to facilitate data simplification, which may be necessary before further processing, and this followed what was reported by (Adebayo et al., 2013; Aweda et al., 2022). However, the refractivity index of the meteorological dataset on the use of neural networks was retrieved for dataset training and testing for forecasting. Furthermore, the model evaluation and validation were matched to the statistically created model for the analysis. Thus, the performance of the proposed model was evaluated utilizing a variety of methodologies, including Mean Average Error (MAE), Root Mean Square Error (RMSE), and R-square.

Consequently, this study focused on wind energy for Nigeria's growth. Nigeria, on the other hand, has been noted as having energy challenges due to poor maintenance of hydro and thermal energy-generating units. In addition, the current research questions are as follows: to determine energy for human consumption, determine statistical analysis for energy generation, determine the performance of the LSTM and bi-LSTM for training and testing datasets, and determine data visualization of other meteorological parameters.

As a result, the current study employs several machine learning algorithms over wind speed data for energy generation in the country in order to tackle the country's energy problem using wind speed data. However, due to insufficient maintenance of hydro energy generating and poor water storage for electricity generation in the country, the study, on the other hand, focuses on a forecasting neural network, a Long Short-Term Memory (LSTM) network model based on several Fire-Work Algorithms (FWA). However, the key advantage of using LSTM models based on FWA models to tackle the country's energy crisis is that the energy generation is based on machine learning, which reduces the country's whole reliance on hydro energy generation and threatens its economy.

3.3. Data collection and description

The authors used Solar Data of Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) meteorological re-analysis for the collection of monthly air temperature, air pressure, relative humidity, wind speed, and direction for nine tropical regions of African stations (Aweda et al., 2020; Aweda et al., 2021; Gelaro et al., 2017). The data was evaluated on January 15th, 2022. From 1985 to 2021, the data was collected in Comma-Separated Value (CSV) format as a monthly average for January to December of each year. The dataset includes the name of the city, latitude and longitude coordinates, and the date of the observation (Figure 2).

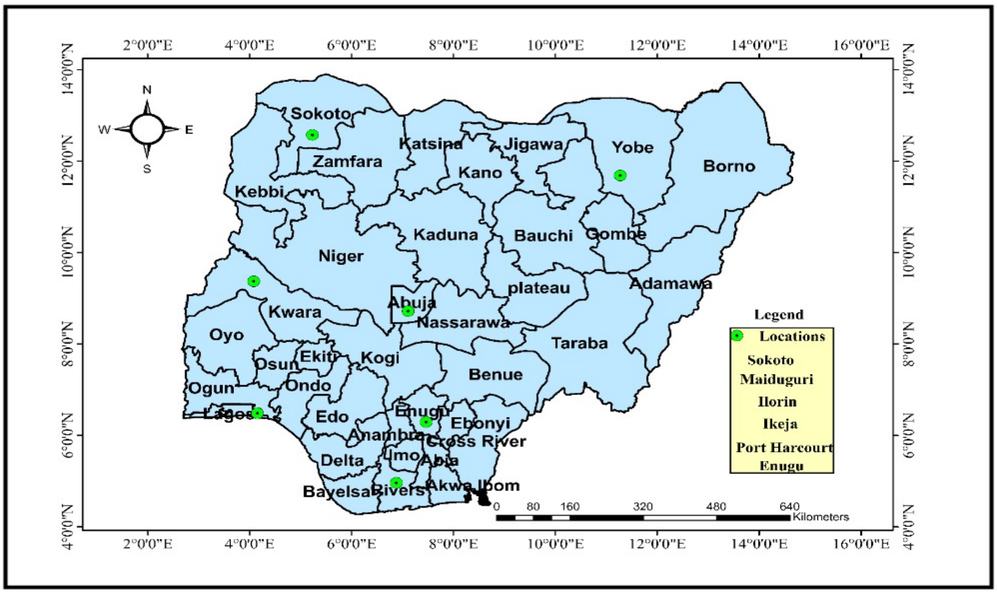


Figure 2. The stations depicted on the map

3.4. The subject of research

The following stations were employed in this study: Abuja, Ilorin, Ikeja, Damaturu, Port Harcourt, and Sokoto. These stations were chosen from throughout the country (Table 2). The effect of meteorological data across the country is demonstrated by dividing these stations into different climate areas.

3.5. Metrics for statistical accuracy

The study employed performance metrics to compute R-Squared, RMSE, and MAE by calculating data training and testing. To determine different machine learning parameters for the analysis, 80 % of the data was trained and 20 % of the data tested. However, from the standpoint of machine learning, data processing, feature selection, modeling, and testing were performed based on the nature of the data and available models for analysis. The prediction error that is related to the model performance of the wind speed dataset was investigated using statistical parameter (R-Squared, RMSE, MAE, MSE). The MAE (mean absolute error) that was employed in this study shows the difference between the expected and actual values. Mean Squared Error (MSE), on the other hand, displays the average value of a dataset by squaring the difference between real and predictable values. Furthermore, when compared to the value of the original dataset, the root means square error reveals that the coefficient of determination (R-squared) reproduces the outcome of the matches in the togetherness. In this case, the percentage and range are presumed to be between 0 and 1. In contrast, it demonstrates that the higher the value of any model, the better the outcome.

Table 2. The stations used and their locations

Stations	Longitude ^{0}N	Latitude ^{0}E
Abuja	9.07	7.49
Ilorin	6.46	7.55
Ikeja	6.61	3.35
Damaturu	11.75	11.97
Port-Harcourt	4.78	17.01
Sokoto	13.01	5.25

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N}\left|y_i - \hat{y}\right| \tag{9}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{t-1}^{N}\left(y_i - \hat{y}\right)^2 \tag{10}$$

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} = \sqrt{\frac{1}{N}\sum_{t-1}^{N}\left(y_i - \hat{y}\right)^2} \tag{11}$$

$$R^2 = 1 - \frac{\sum\left(y_i - \hat{y}\right)^2}{\sum\left(y_i - \bar{y}\right)^2} \tag{12}$$

where $\hat{y}$ – the predicted value of y, $\overline{y}$ – mean value of y.

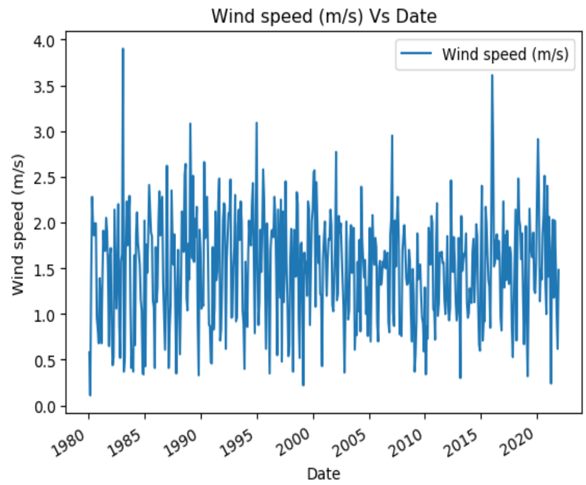
2.6. Normalization of wind speed processes

$$X_{nor} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{13}$$

Equation 12 is the normalization formula used in the study. X_{nor} represents the normalization, X_{max} the maximum value of the wind speed data, and X_{min} the minimum value of the wind speed data used in the study.

4. RESULTS AND DISCUSSION

The following stations are labeled based on the results reported in the manuscript as shown in Figure 3 (a to f) as in a-Abuja, b-Ilorin, c-Ikeja, d-Maiduguri, e-Port-Harcourt and f-Sokoto. This displays the wind speed data after the machine learning method has filled in the nulls. The findings indicate that practically every considered station has an almost similar pattern. This demonstrates that all stations in Nigeria have the same wind speed pattern.



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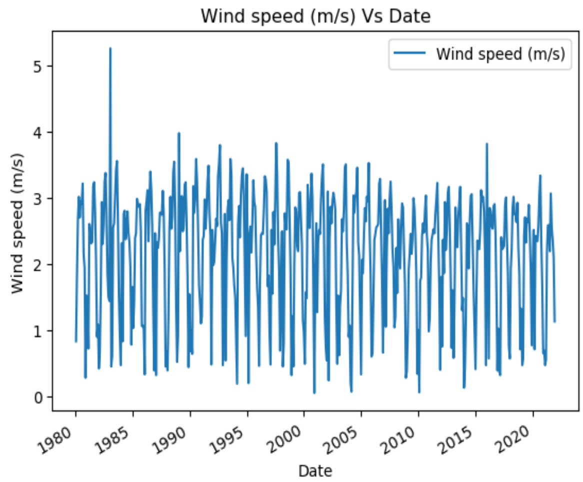

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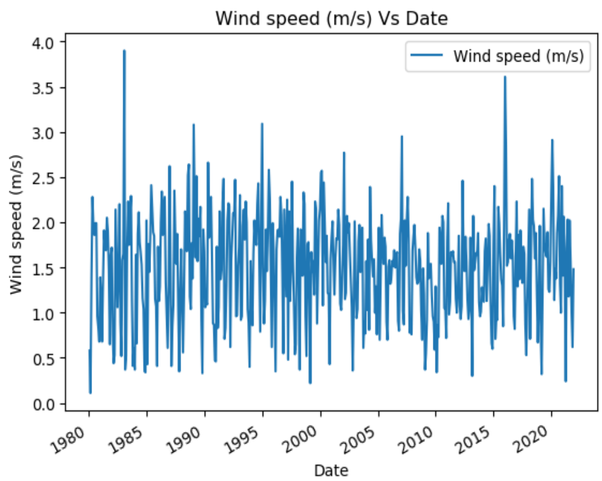

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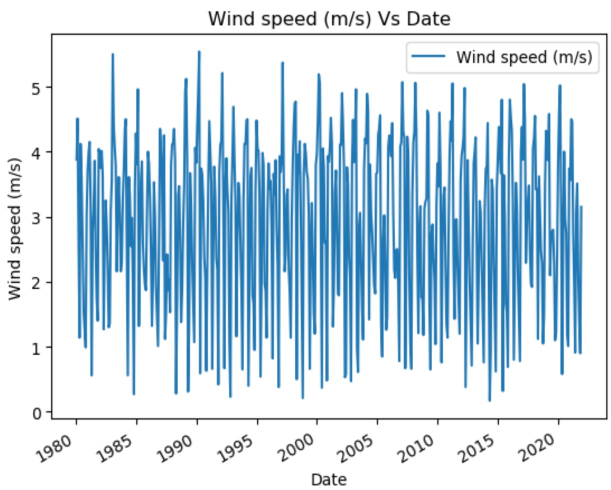

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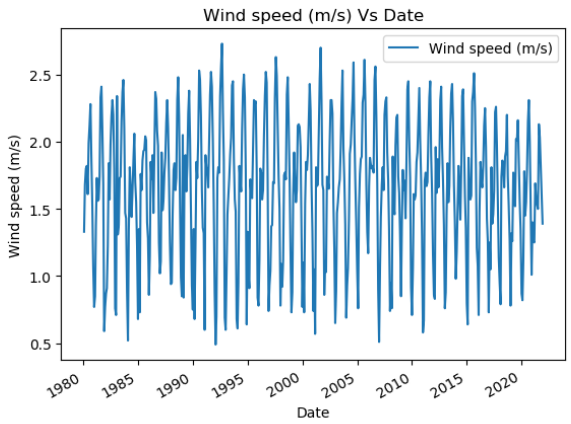

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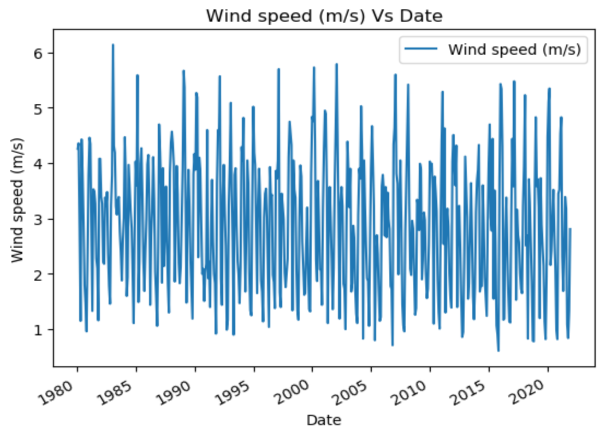
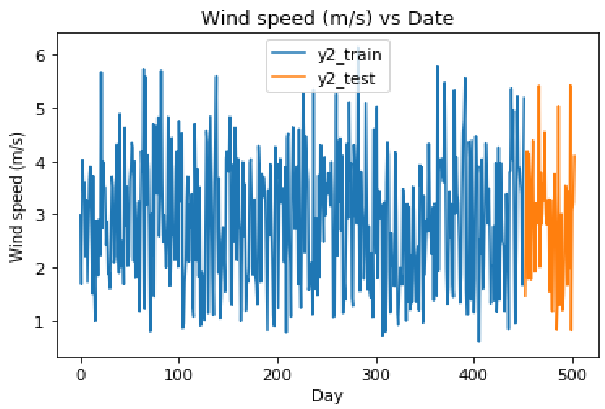


(f)

Figure 3. Wind speed after the machine learning method has filled in the nulls

The result in Figure 3 (a to f) demonstrates that the pattern of wind speed at each station is nearly identical, indicating that the wind speed at the chosen station moves at a similar pace, which can increase the production of wind energy across the entire nation. However, during the period when energy output from wind is increasing, short-term wind speed predictions are crucial. Furthermore, Figure 3 (a to f) shows the wind speed vs date for the stations under investigation. The maximum wind speed for the stations was found to be between (6.5-2.6 m/s), while the minimum wind speed was found to be between (0.2-1.0 m/s). This demonstrates that the wind speed for energy generation in the reported stations is low.

Figure 4 (a to f) shows the dataset split ratio into trained and tested, demonstrating that 80 % of the dataset is used for training and the remaining 20 % for the purpose test set. However, several writers have stated that the test and trained data are critical when using machine learning to model wind speed. The trained data for this study covers the years 1985 to 2014, whereas the test data covers the years 2015 to 2021; this equates to 30 years of training and 7 years of testing. However, the training of the data set takes longer than the testing. Furthermore, if the numerical value of the samples was adequate, the sampling techniques for this research dataset would be balanced. According to authors (Junior & do Carmo Nicoletti, 2019; Rojas, 2009), if approaches like Boosting and AdaBoost are employed for any study, the number of data sets used will be sufficient. Each of the samples utilized, however, participates in the training and testing operations of the dataset, being separated into parts, and the other portions participate in the dataset training, as reported in (Junior & do Carmo Nicoletti, 2019; Rojas, 2009). By averaging the accuracy rates used to obtain each classification technique, the outcome validation for each piece of data testing at each phase may be done.



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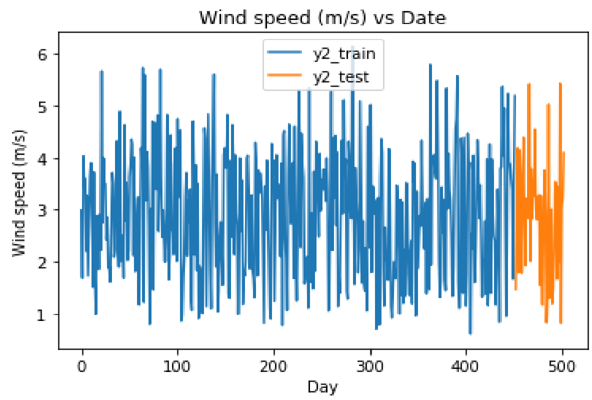

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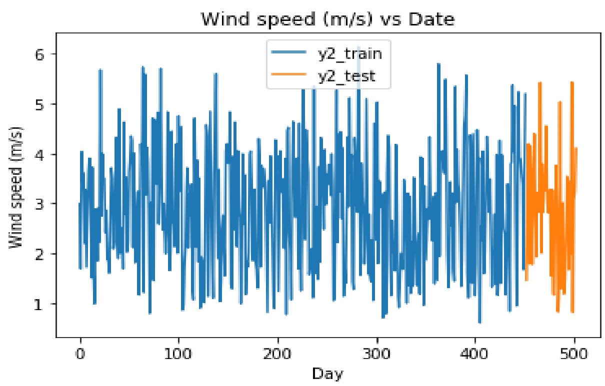

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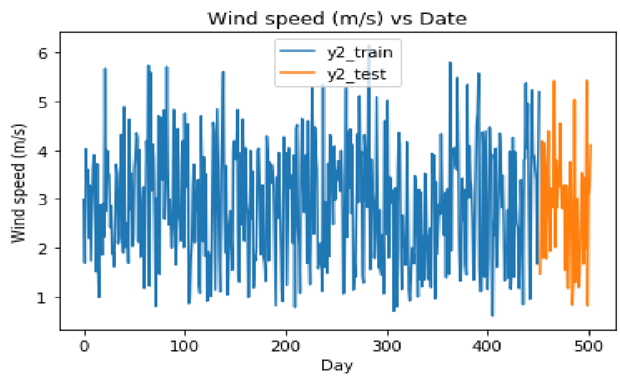

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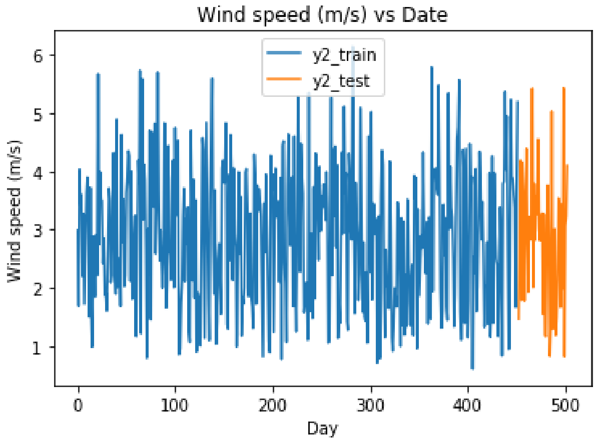

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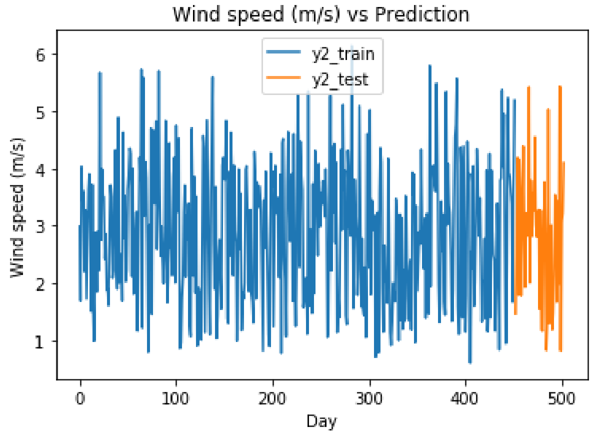


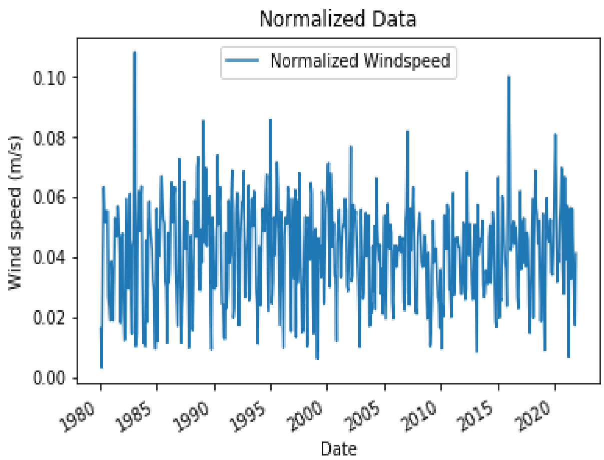
(f)

Figure 4. Training and testing of the wind speed over the selected stations

As shown in Figure 4 (a to f), the data for the study were divided into two sets: testing and training. The sample data was examined, and the first 80 % of the data was used for training, as revealed by the LSTM network model, according to the validation procedure. The remaining 20 % of the data was utilized as the prediction data to verify the model efficiency.

Results in Figure 4 show that the training data had more input than testing data. However, this demonstrates that the training data are more important than testing data. Moreover, the training data indicate that the wind speed performs better.

Figure 5 shows data normalization using Equation 12. This is used to process wind speed data (Junior & do Carmo Nicoletti, 2019; Rojas, 2009) for samples with values ranging from 0 to 1. Figure 5 depicts the process data, showing a high peak in 1985 (a = 0.12 m/s, b = 0.11 m/s, c = 0.13 m/s, d = 0.08 m/s, e = 0.06 m/s, f = 0.10 m/s). The results reported in Figure 4 (a to f) are based on training and testing data sets that span 36 years. However, the figure was plotted using 500 days. This is because the data was normalized. The train days were approximately 450 days, while the test data was approximately 50 days.



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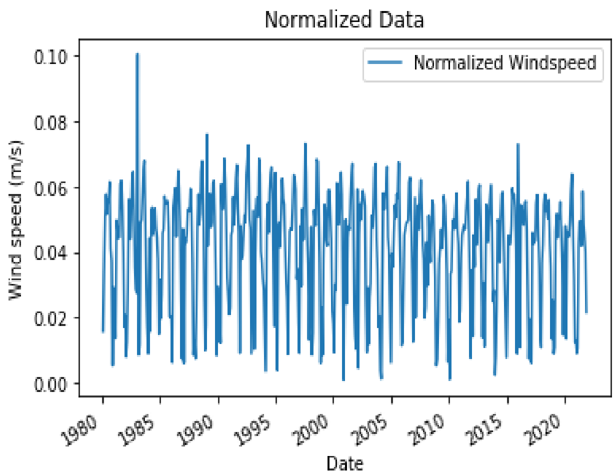

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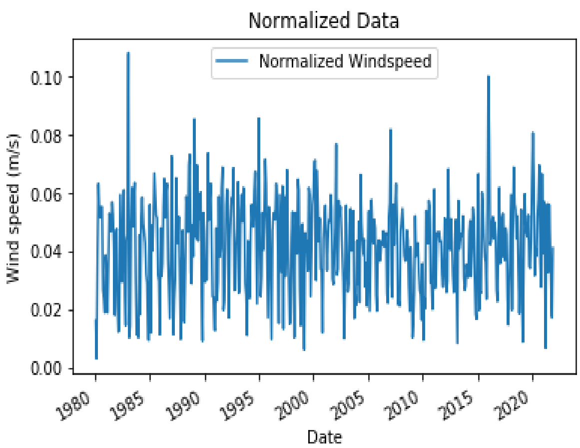

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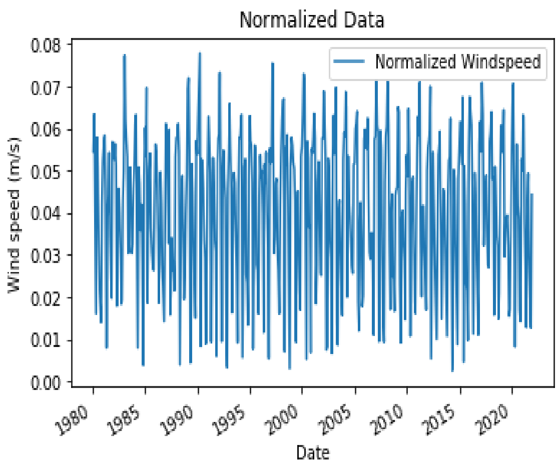
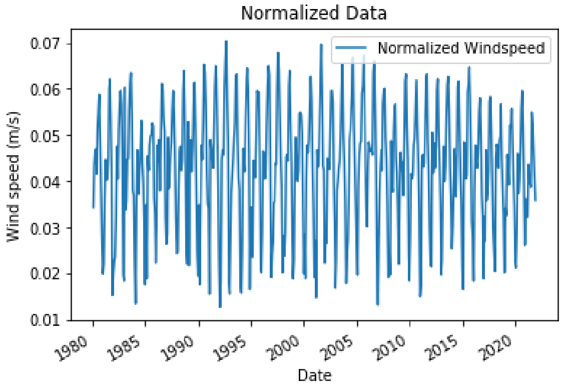
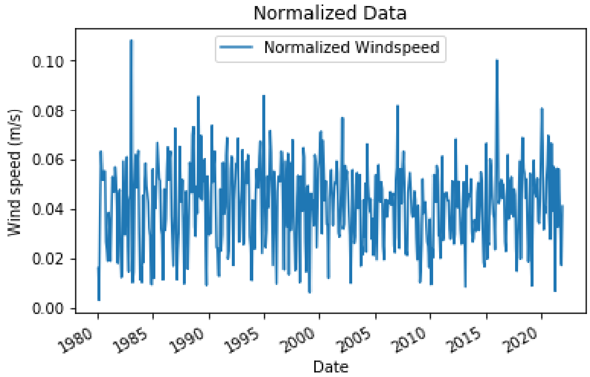


(d)



(e)



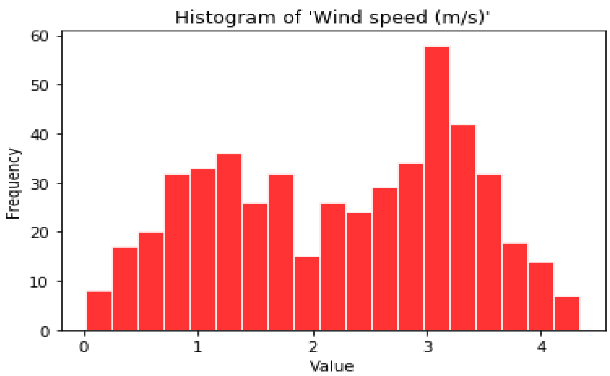
(f)

Figure 5. Normalization of wind speed processes over selected stations

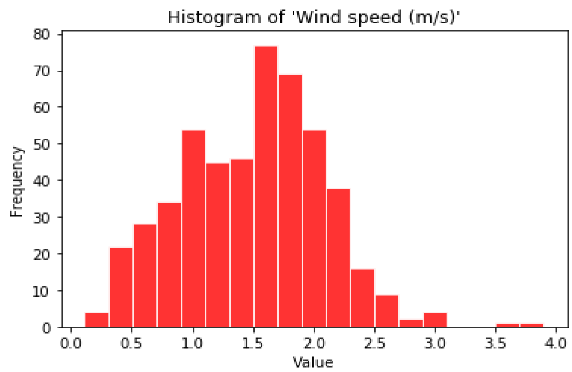
The range standardization process for wind speed data, which ranges from 0 to 1, is demonstrated by the data normalization and is based on the computation method used during the range standardization (Shao et al., 2021). However, as reported by authors in (Shao et al., 2021), the training of the LSTM network model and the first 80 % of the data are used as the training data. The remaining 20 % of the data are utilized as prediction data to assess the model effectiveness. The outcome thus demonstrates the significance of wind speed and direction in energy generation forecasting, which could result in the production of energy across the entire country. Wind speed normalization, in particular, demonstrates that the data are typically adjusted for the aim of energy production.

4.1. The theoretical frequency of wind speed

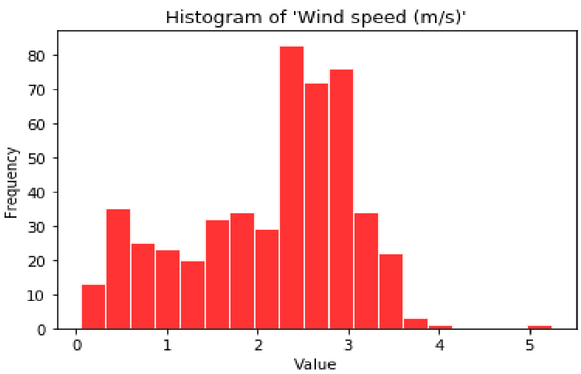
By exhibiting relative frequencies associated with the stations under investigation as shown in Figure 6 (a to f), the histogram shows that the dataset is standardized. The fraction of cases that fall into multiple categories is equal to 1 according to the findings. Abuja has a maximum frequency of 70 and a minimum frequency of around 8. Ilorin, on the other hand, has a maximum frequency of roughly 76 and a low frequency of around 3. Other stations, as indicated in Figure 6, appear to follow the same pattern. The reported results revealed that the frequency of wind speed was critical. The findings point to this conclusion that the categories of consecutive, non-consecutive, and non-overlapping variable intervals with categories (intervals) are contiguous, and they are all of the same size, as shown in the figures. Each of the indicators continuously has its original variables, as shown by the histogram rectangle. However, the result shows that none of the best numbers is bins, denoting different size bins, as some data reveals. The theoretical bin demonstrates that the optimal number of data bins is determined from various attempts. The bin with widths adequate for the experimentation of the dataset utilized in the result is denoted by the distribution dependence and the analysis purpose.



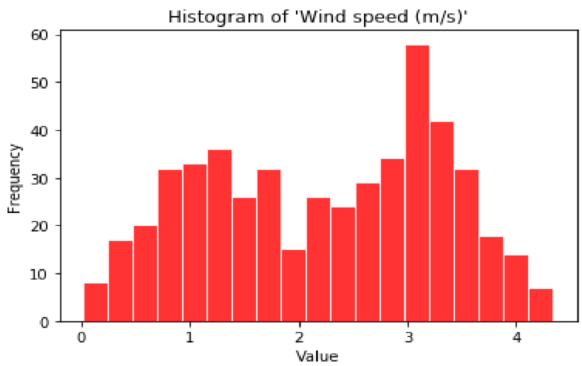
(a)



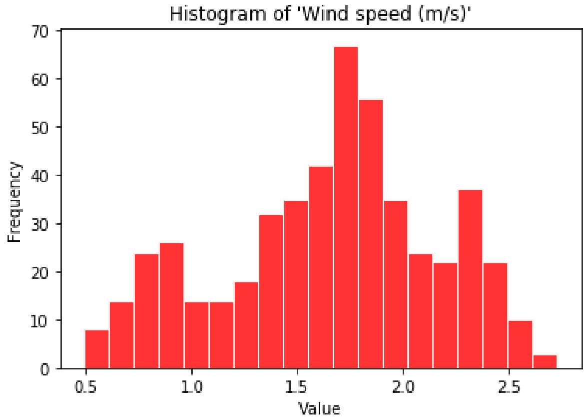
(b)



(c)



(d)



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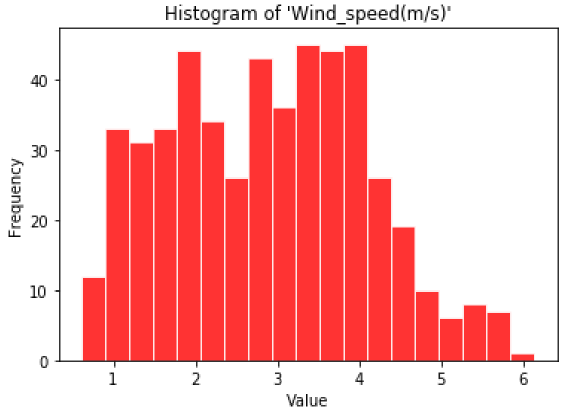


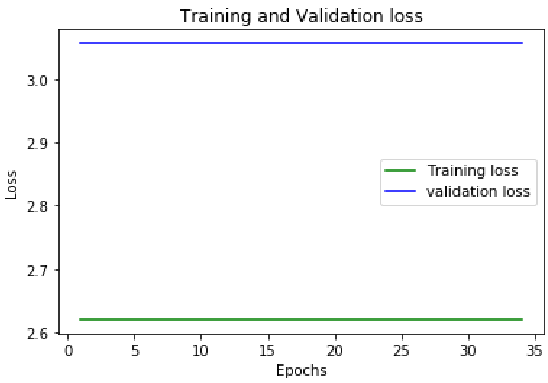
(f)

Figure 6. Frequency dataset of the wind speed

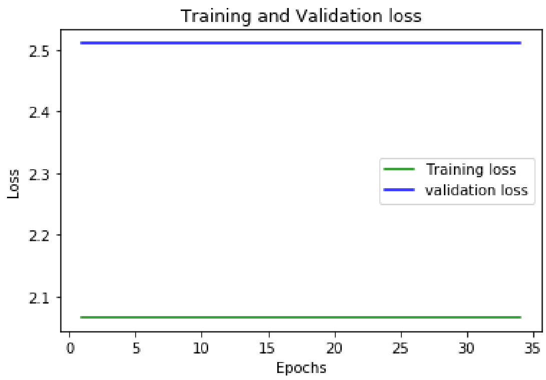
The frequency result of the wind speed data demonstrates that wind speed contributes significantly to the outcome of energy production. However, the frequency result demonstrates that good energy generation occurs when the data are well correlated, which will increase the country's overall energy production.

4.2. Wind speed prediction using basic LSTM

The core four layers of the LSTM model as shown in Figure 7 (a to f), each with one input layer and two hidden levels each with one output layer, are used to forecast wind speed. That is, the connection among the three layers of the LTSM is established by the 1st layer of the LTSM, which receives an input time step of variable 1, but has 64 neurons, as stated in (Shao et al., 2021). The input of the training data transforms into its output, which appears after the hidden layer as the 2nd layer used in this study. In addition, the input of the training transforms into its output, which appears after the hidden layer as the third layer used in this study. The number of neurons in this study indicates that the first layer has the same pattern as in Figure 7 and that the third layer (Dense) uses the first layer of the long short-term memory for the output layer of the third layer, as shown in the result. The output of the 2nd layer is similarly received by the 3rd layer, which is shown as input, and the connection is the result of the connected layer. The results of the studied stations show that a one-dimensional vector with a length of 150 output data sets is connected in the learning for the final output of future data sets. The output results provided 150 data points, as shown in Figure 7. The hidden layer is used to regularize the 2nd layer, as shown in the image, and the LSTM is used to validate the dropout layer of the data that was added to the 1st layer, confirming what was reported by the previous layer (Shao et al., 2021). According to the results of the tests, the accuracy of the training set with the greatest dropout of 0.2 s was discovered (Ma et al., 2021; Shao et al., 2021).



(a)



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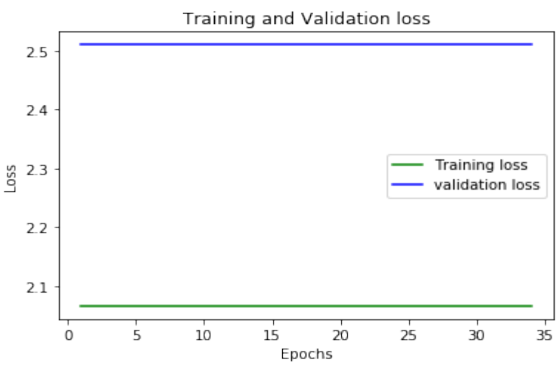
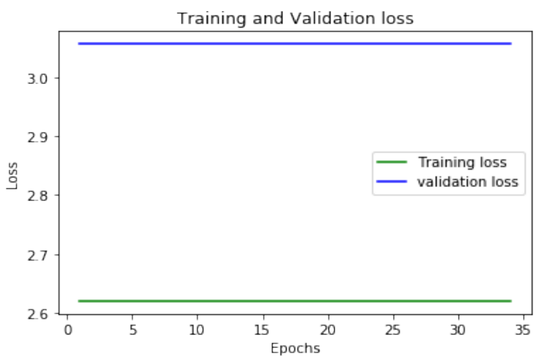
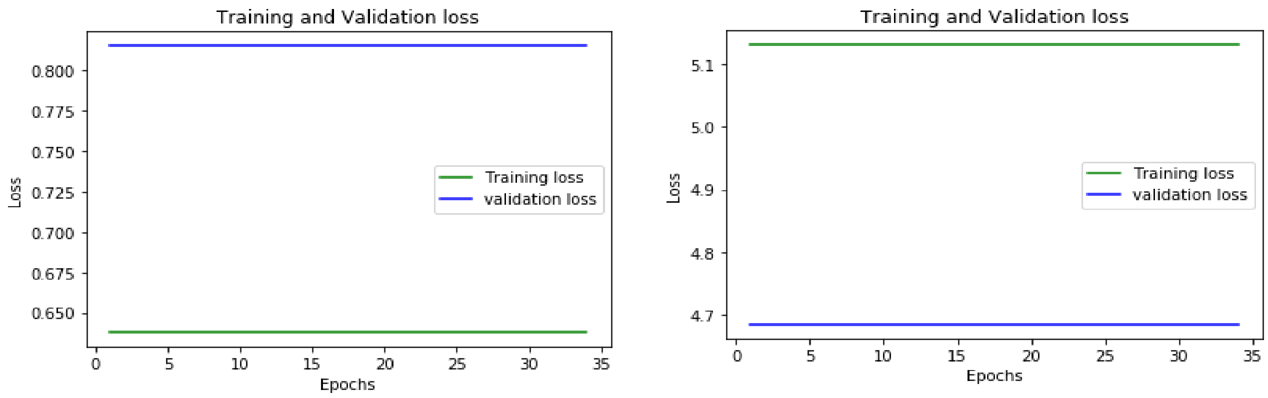


(c)



(d)

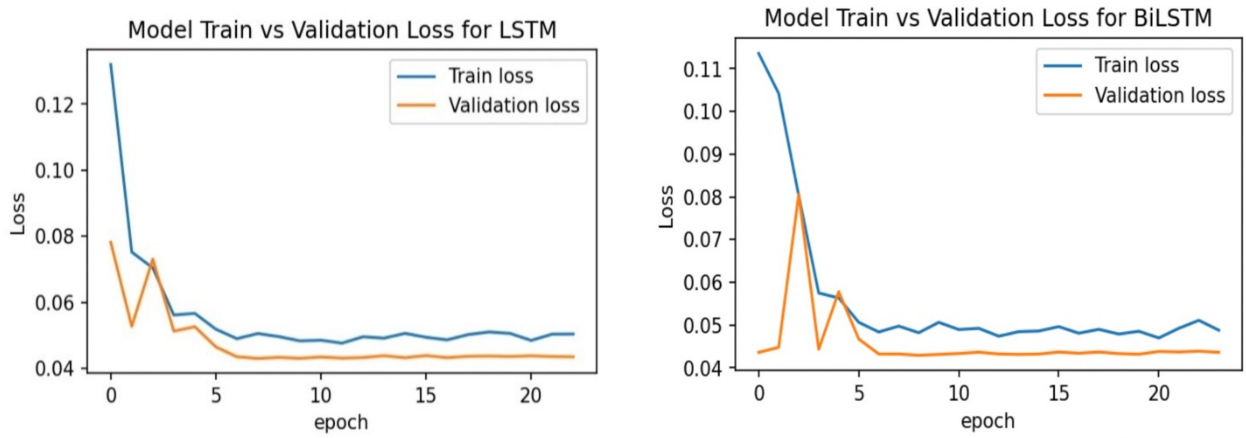


(e) (f)

Figure 7. The performance of the LSTM and bi-LSTM for training and testing datasets

The performance of the bidirectional long-short term memory (bi-LSTM) may be seen in this result, where the training and validation loss line is always close to one and the loss is virtually zero. The model, on the other hand, is of well-trained validation. The Recurrent Neural Network (RNN), LSTM, and bi-LSTM works were found useful in the investigation of wind speed validation and training in this study. As a result, each of the models employed in this study is unique. Finally, the step-by-step approach yielded a simple bi-LSTM model for text classification following what was reported by (Samadianfard et al., 2020). The data set, on the other hand, was idle for the categorization process, and most of the models demonstrate a real-life problem solution for the research of wind patterns at the specified study stations. More specifically, the model investigates what happened with the real-world wind speed data issue. As a result, it will text data, audio data, and time series data for the benefit of the outcome.

The LSTM and bi-LSTM research indicate that the wind energy forecast will increase product knowledge for the improvement of energy generation. If this is put to use, it will aid in the decrease of the energy problem that the entire nation is currently experiencing. Additionally, given that energy is a major problem throughout the world, LSTM and bi-LSTM will account for a significant energy generation to lessen the burden placed on hydroelectric energy output.



(a) (b)

Figure 8. Model training performance against validation loss

Figure 8 shows the difference in wind speed prediction performance among LSTM, BiLSTM, and GRU in terms of training and validation loss. The minimum training and validation cost (loss) functions are 0.04 and 0.045 at the 4th epoch for BiLSTM, 0.043 and 0.046 at the 5th epoch for LSTM, and 0.05 and 0.01 at the 6th epoch for GRU. This demonstrates that although having the lowest cost function, the GRU model has a faster convergence time. To avoid model overfitting, the training process was terminated when the validation error trend shifted from dropping to climbing; this followed what was reported by authors in (Moghadasi et al., 2021).

4.3. The training algorithm's performance

Table 3 presents the summary result of the performances of the different 11 Machine Learning algorithms of regression type for each of the seven locations in Nigeria. For Abuja, Coarse Tree, Ensemble Bagged Trees, and Gaussian-Squared Exponential GPR show the highest R^2 of 0.44, while for Enugu, it was medium Tree ($R^2 = 0.74$). Result reveals that in Ikeja, Gaussian-Squared Exponential GPR and Rotational Quadratic GPR ($R^2 = 0.37$); for Ilorin, R^2 = Ensemble Boosted Trees; for Maiduguri, it was Narrow Neural Network; for Port-Harcourt, it was Medium Gaussian SVM ($R^2 = 0.81$), while for Sokoto, the Narrow Neural Network that gave the highest R^2 ($R^2 = 0.68$). This implies that these ML algorithms exhibit better fitness performance than other models. In terms of forecasting performance of these ML algorithms based on RMSE, the best forecasting Machine Learning model was Ensemble Bagged Trees for Ikeja (RMSE = 0.10299); Medium Tree for Enugu (RMSE = 0.0876); Gaussian-Squared Exponential GPR and Rotational Quadratic GPR for Ikeja (RMSE = 0.11969). Result reveals that Ensemble Boosted

Trees give the least RMSE for Ilorin (RMSE = 0.10651), Narrow Neural Network for Maiduguri (RMSE = 0.1029), Medium Gaussian SVM for Port-Harcourt (RMSE = 0.10115), and Ensemble Boosted Trees for Sokoto (RMSE = 0.1218), meaning that these ML algorithms outperformed other models.

Table 3. Summary result of the machine learning Algorithm (MLA) for wind speed data across selected stations in Nigeria

Different Models Used	**Abuja**			**Enugu**			**Ikeja**			**Ilorin**		
Machine Learning Algorithm	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**
Medium Tree	0.40	0.10681	0.081377	0.74	0.087688	0.065278	0.31	0.12486	0.088858	0.79	0.11676	0.089249
Coarse Tree	0.44	0.10312	0.080436	0.55	0.11562	0.09035	0.33	0.12353	0.090195	0.75	0.12643	0.10061
Fine Gaussian SVM	0.33	0.11301	0.085718	0.68	0.097669	0.071186	0.31	0.12535	0.090072	0.77	0.12161	0.092987
Medium Gaussian SVM	0.40	0.10645	0.084072	0.63	0.1041	0.076264	0.31	0.12551	0.093378	0.77	0.1233	0.096499
Ensemble Boosted Trees	0.36	0.10974	0.08792	0.68	0.096728	0.071891	0.33	0.12295	0.090359	0.83	0.10651	0.082177
Ensemble Bagged Trees	0.44	0.10299	0.081808	0.67	0.098439	0.0747	0.36	0.12066	0.0936	0.77	0.12106	0.09426
Gaussian-Squared Exponential GPR	0.44	0.10312	0.080436	0.66	0.10076	0.077159	0.37	0.11969	0.087037	0.79	0.11705	0.0911044
Gaussian-Matern 5/2 GPR	0.38	0.10814	0.085041	0.66	0.10076	0.077127	0.36	0.12538	0.092184	0.79	0.1175	0.091995
Exponential GPR	0.37	0.10937	0.085171	0.67	0.099089	0.075147	0.31	0.12086	0.088137	0.79	0.11759	0.091529
Rotational Quadratic GPR	0.39	0.10736	0.084767	0.66	0.10082	0.077192	0.37	0.11969	0.08707	0.79	0.11723	0.091341
Narrow Neural Network	0.39	0.10764	0.08163	0.71	0.093159	0.067218	0.36	0.12493	0.095756	0.79	0.11665	0.090558
Bidirectional LSTM	-0.0024	0.5298	0.4141	-0.0002	0.8609	0.7271	-3.6399	9.6416	8.5489	-0.0243	0.8712	0.6876
LSTM	-0.0792	0.5497	0.4405	-0.0080	0.8642	0.7471	-3.5740	9.5729	8.4762	-0.0289	0.8731	0.6846
GRU	-0.0025	0.5298	0.4143	-0.0017	0.8615	0.7361	-3.5788	9.5778	8.4802	-0.0178	0.8684	0.6928

Different Models Used	**Maiduguri**			**Port-Harcourt**			**Sokoto**		
Machine Learning Algorithm	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**
Medium Tree	0.78	0.10669	0.08342	0.80	0.10463	0.078763	0.62	0.12971	0.094396
Coarse Tree	0.74	0.117	0.093373	0.68	0.13324	0.10785	0.56	0.1394	0.10293
Fine Gaussian SVM	0.73	0.11877	0.087973	0.78	0.11094	0.082671	0.62	0.12885	0.091896
Medium Gaussian SVM	0.67	0.13115	0.10104	0.81	0.10115	0.077071	0.56	0.13886	0.11089
Ensemble Boosted Trees	0.78	0.10768	0.082073	0.77	0.1118	0.086639	0.66	0.1218	0.090333
Ensemble Bagged Trees	0.75	0.1131	0.090676	0.80	0.10471	0.081664	0.59	0.13391	0.10418
Gaussian-Squared Exponential GPR	0.77	0.10981	0.083424	0.80	0.110449	0.077995	0.66	0.12242	0.90771

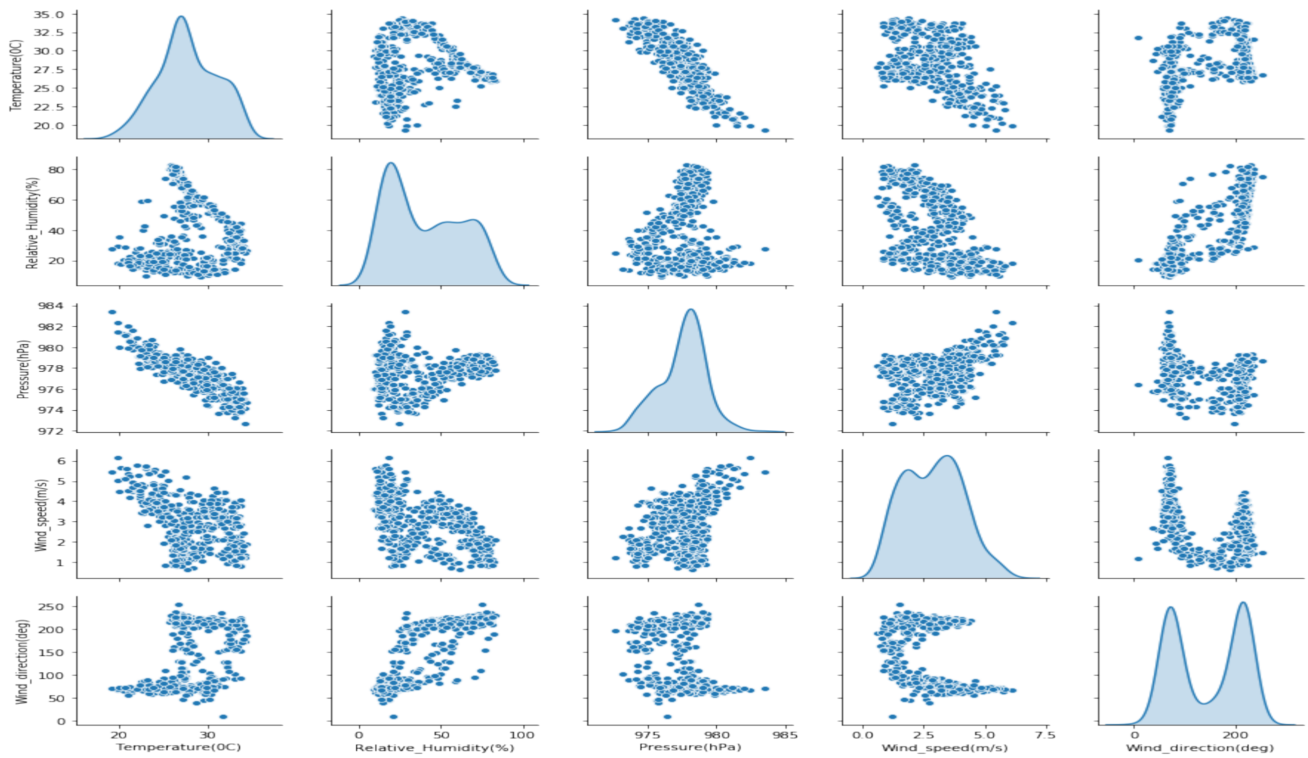
Gaussian-Matern 5/2 GPR	0.77	0.10925	0.084038	0.80	0.10422	0.077357	0.66	0.12208	0.089877
Exponential GPR	0.77	0.1086	0.083315	0.80	0.10463	0.077443	0.66	0.12276	0.090102
Rotational Quadratic GPR	0.77	0.10981	0.083424	0.80	0.10437	0.07769	0.66	0.12242	0.090771
Narrow Neural Network	0.80	0.1029	0.081107	0.79	0.10652	0.077358	0.68	0.12444	0.096222
Bidirectional LSTM	-0.0330	1.2208	1.0137	-0.0321	0.4111	0.3304	-0.0319	1.3147	1.0921
LSTM	-0.0691	1.2419	1.0248	-0.0470	0.4140	0.3323	-0.0283	1.3124	1.0904
GRU	-0.0882	1.2530	1.0305	-0.0139	0.4074	0.3293	-0.0351	1.3168	1.0936

Furthermore, the performance of LSTM, BiLSTM, and GRU models is shown in Table 3 using three assessment metrics: R^2, MAE, and RMSE. The neurons in the hidden layers, as well as the hyper-parameter turning, significantly affect the architecture of the models. The number of hidden layers was modified from two to five to achieve the best architecture, with each layer holding thirty neurons. The average coefficients of determination (R^2) for all the stations observed for LSTM, BiLSTM, and GRU with two layers are -0.548, -0.538, and -0.534, respectively. This demonstrates that the three models outperform the other models used. Furthermore, as the model complexity increases, so does its performance. The MAE and RMSE statistics show that as the number of neurons increases, GRU and BiLSTM tend to marginally reduce prediction errors in comparison to the LSTM neural network model. GRU outperformed both the BiLSTM and LSTM by a narrow margin. Table 4 further demonstrates that wind speed prediction using GRU with one hidden layer has the lowest MAE and RMSE.

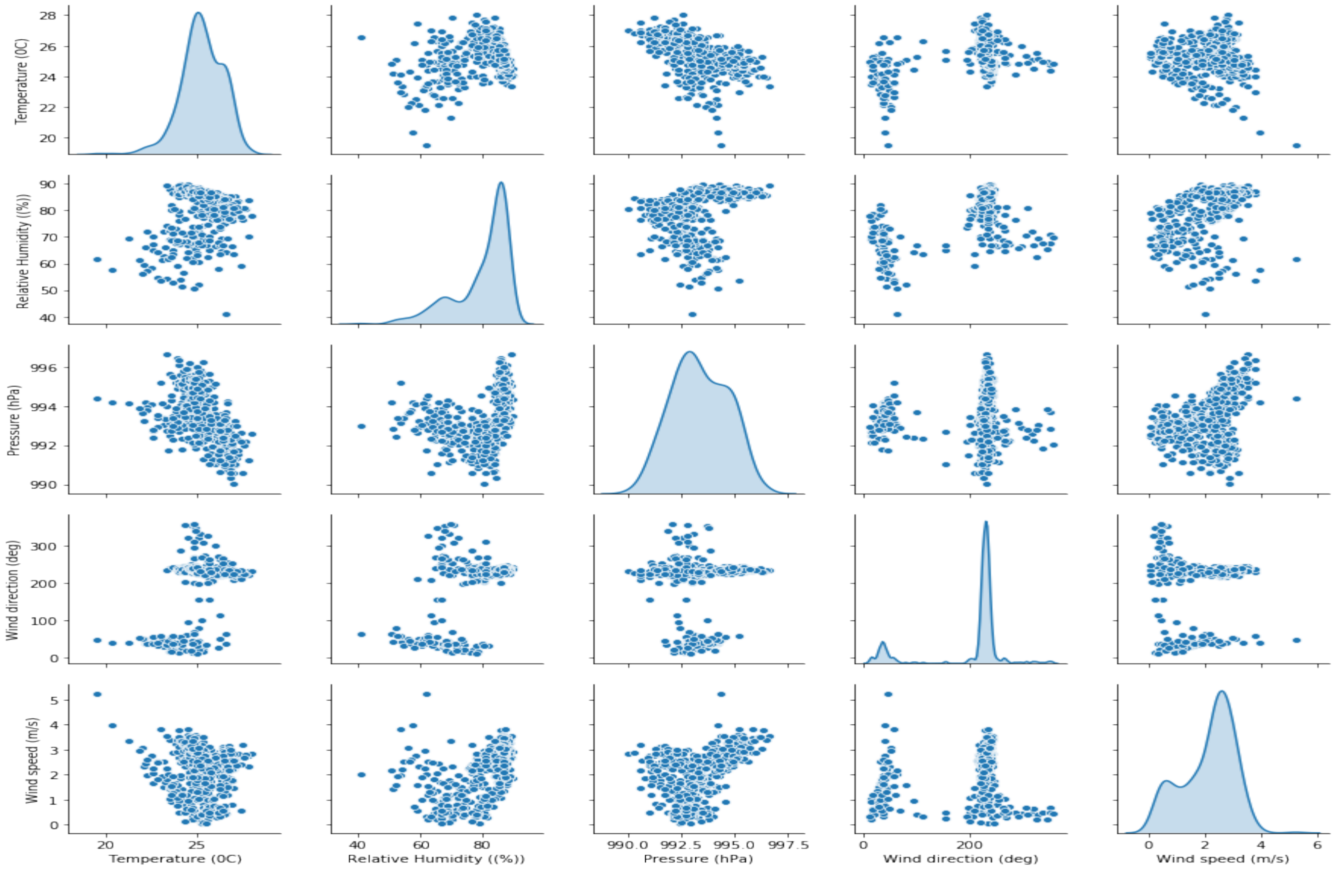
The pair plots of meteorological data utilized for wind speed prediction are shown in the resulting Figure 9 (a to f). It was discovered that the tools swiftly investigated how to distribute the dataset and the relationships within it.

The sea born, on the other hand, demonstrates that the pair plot of the dataset is the easy default way. As seen in Figure 9, wind speed against temperature has a fragmented dataset for all of the stations studied. The customized extended pair grid, on the other hand, demonstrates that the dataset is a significant component of the value, which is derived not from showy machine learning but the visualization of the dataset. A pair plot is a powerful tool for analyzing large datasets. This aids in the display of the weather data.

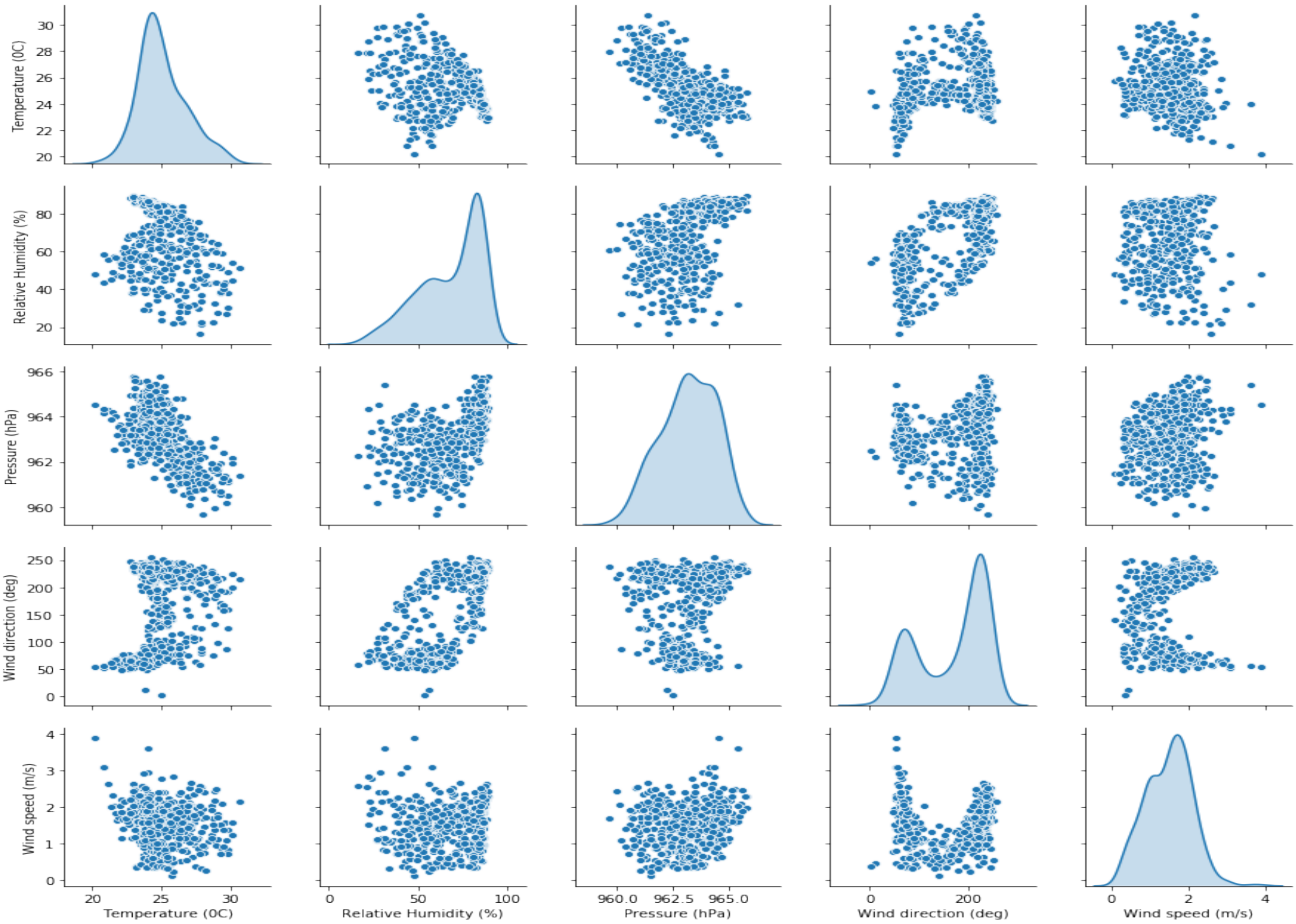
Table 4 displays the descriptive statistics analysis of the variability of wind speed data for the chosen stations. The results show that the maximum wind speed recorded was 6.14 at Sokoto in January with a standard deviation of 0.74, while the minimum wind speed recorded was 0.10 at Ilorin in December, with a standard deviation of 0.61. However, this demonstrates that Sokoto is Iran's north, whereas Ilorin is Iran's centre. As a result, high wind speed in the north and low wind speed in the south of the country are given.



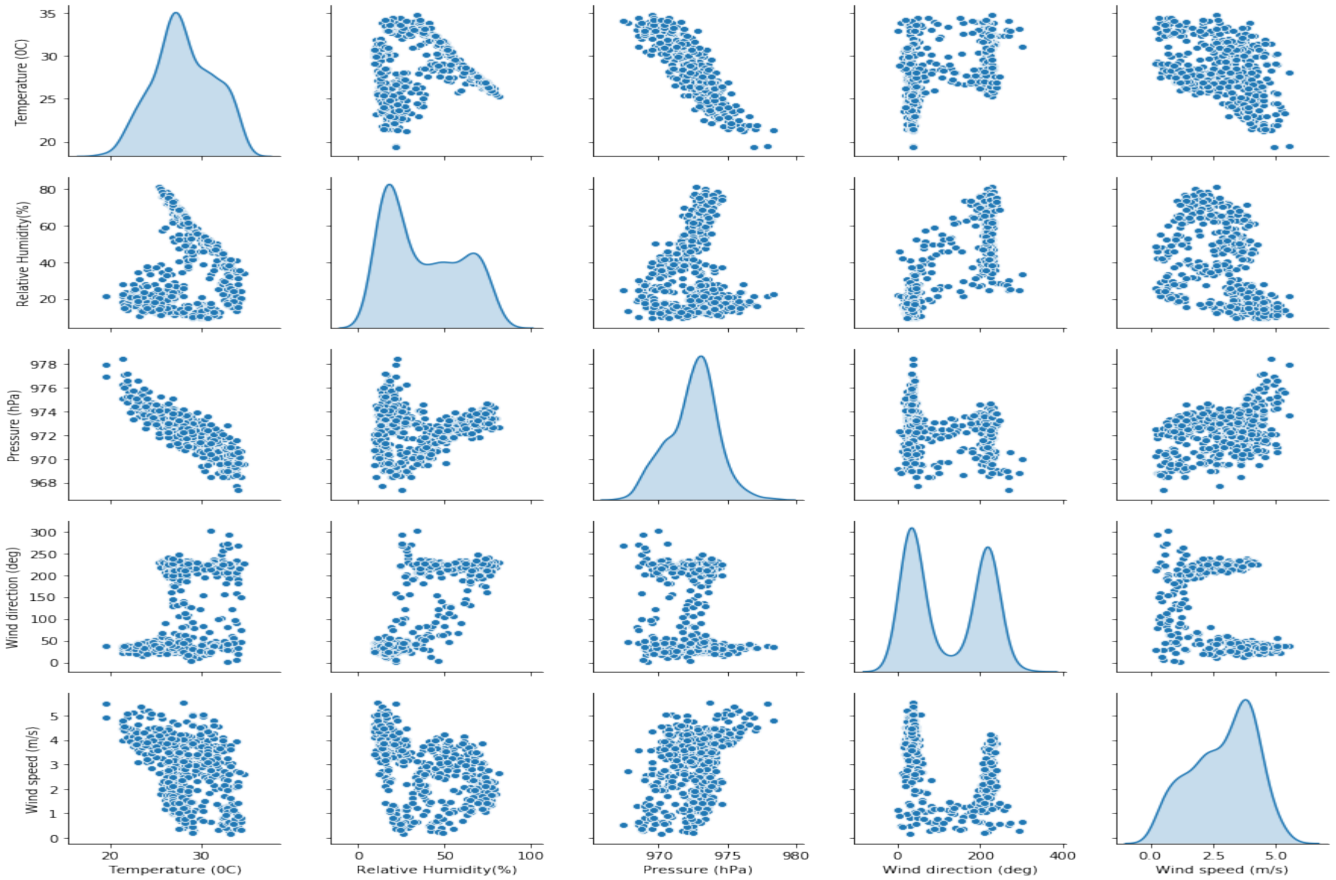
(a)


Temperature (0C)
Relative Humidity ((%))
Pressure (hPa)
Wind direction (deg)
Wind speed (m/s)

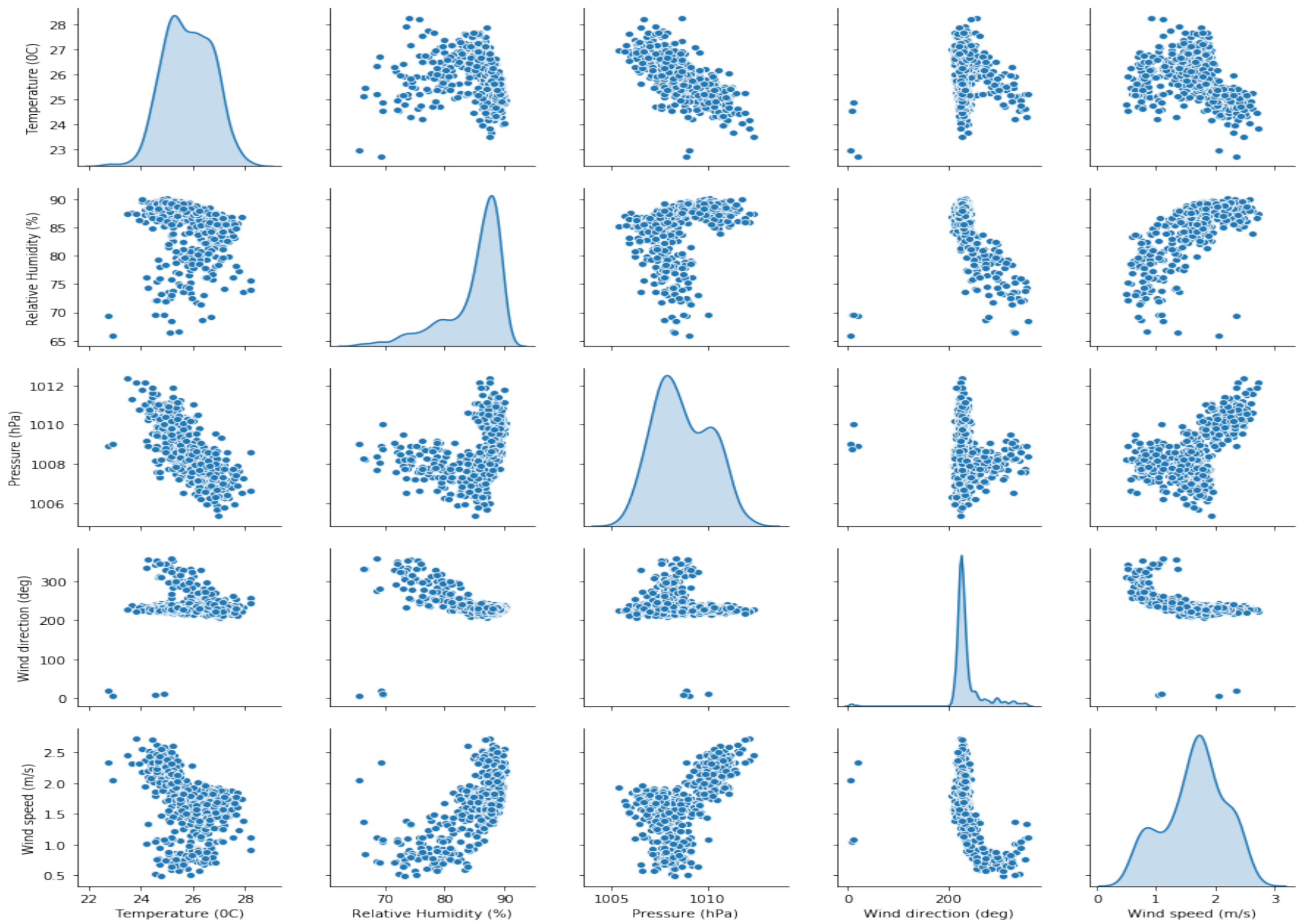
(b)


Temperature (0C)
Relative Humidity (%)
Pressure (hPa)
Wind direction (deg)
Wind speed (m/s)

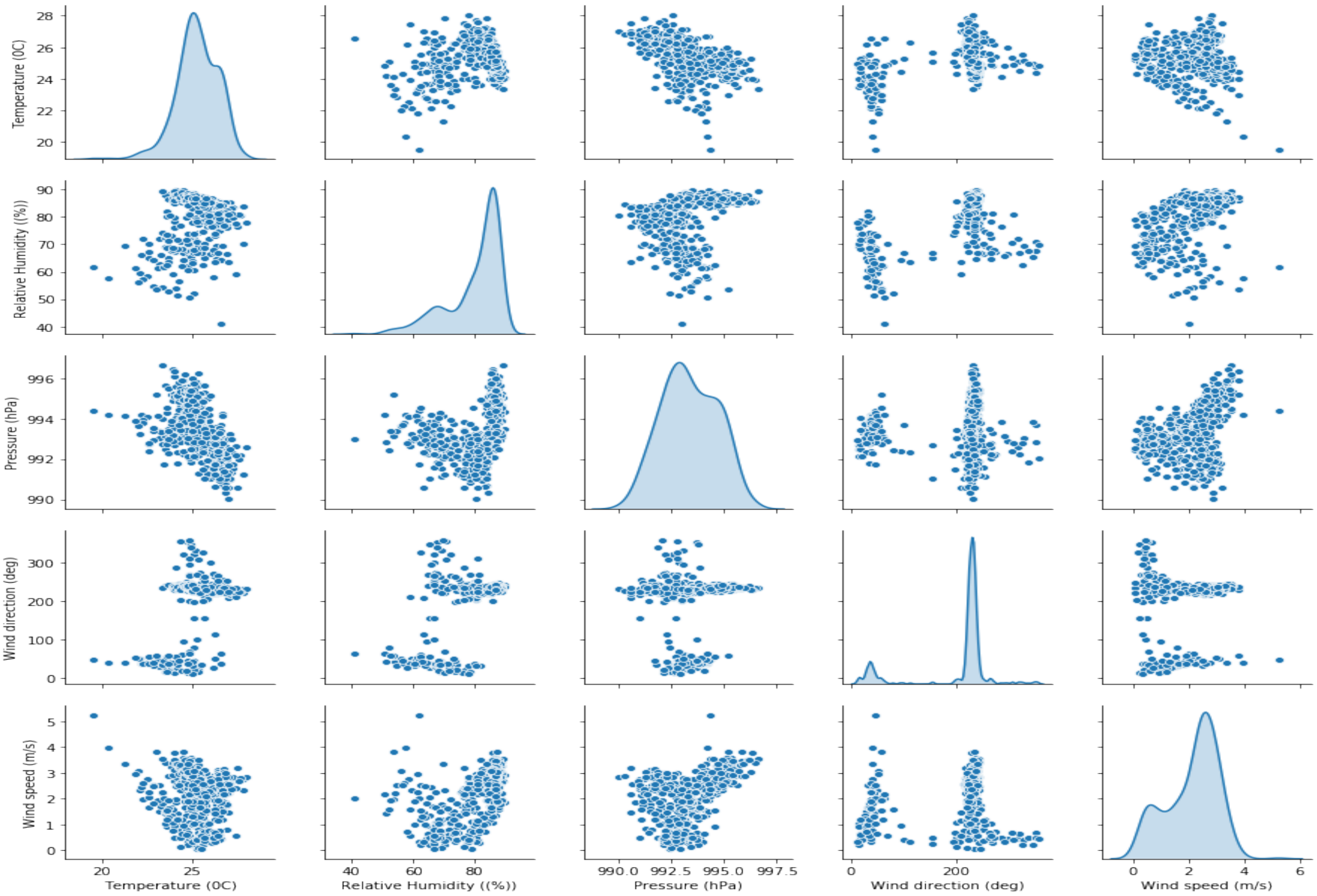
(c)


Temperature (0C)
Relative Humidity(%)
Pressure (hPa)
Wind direction (deg)
Wind speed (m/s)
Temperature (0C)
Relative Humidity(%)
Pressure (hPa)
Wind direction (deg)
Wind speed (m/s)

(d)


Temperature (0C)
Relative Humidity (%)
Pressure (hPa)
Wind direction (deg)
Wind speed (m/s)
Temperature (0C)
Relative Humidity (%)
Pressure (hPa)
Wind direction (deg)
Wind speed (m/s)

(e)



(f)

Figure 9. Data visualization of the meteorological parameters

Table 4. Summary result of the statistical evaluation for wind speed data across the selected stations in Nigeria

Months	Abuja				Enugu				Ikeja				Ilorin			
	Min	**Max.**	**Mean**	**STD**	**Min**	**Max.**	**Mean**	**STD**	**Min**	**Max.**	**Mean**	**STD**	**Min**	**Max.**	**Mean**	**STD**
Jan.	0.34	3.90	0.83	1.63	0.06	5.25	1.42	1.15	0.34	3.90	1.63	0.83	0.13	4.15	1.32	0.90
Feb.	0.11	2.57	0.65	1.10	0.07	2.80	1.35	0.79	0.11	2.57	1.10	0.65	0.02	3.07	1.44	0.82
Mar.	0.24	2.07	0.45	1.20	0.61	2.94	2.22	0.58	0.24	2.07	1.20	0.45	0.34	3.91	2.55	0.91
Apr	0.92	2.66	0.38	1.92	2.15	3.19	2.70	0.27	0.92	2.66	1.92	0.38	2.09	4.34	3.53	0.46
May	1.13	2.41	0.29	1.76	1.93	2.98	2.48	0.24	1.13	2.41	1.76	0.29	2.25	4.11	3.11	0.41
Jun.	1.06	2.18	0.27	1.68	2.19	3.32	2.72	0.26	1.06	2.18	1.68	0.27	2.31	3.57	2.92	0.35
Jul.	1.40	2.58	0.31	1.94	2.63	3.82	3.13	0.28	1.40	2.58	1.94	0.31	2.67	3.93	3.24	0.36
Aug.	1.16	2.64	0.38	1.86	2.47	3.79	3.18	0.28	1.16	2.64	1.86	0.38	2.31	4.16	3.21	0.48
Sept.	0.61	1.65	0.20	1.07	2.09	3.08	2.54	0.25	0.61	1.65	1.07	0.20	1.43	3.16	1.96	0.38
Oct.	0.33	1.48	0.27	0.77	1.06	2.46	1.80	0.31	0.33	1.48	0.77	0.27	0.77	2.19	1.28	0.32
Nov.	0.34	2.40	0.55	1.27	0.05	1.82	0.80	0.43	0.34	2.40	1.27	0.55	0.15	1.98	0.86	0.47
Dec.	0.37	3.61	0.55	1.76	0.13	3.81	1.32	0.76	0.37	3.61	1.76	0.55	0.10	3.31	1.32	0.61

Months	Maiduguri				Port-Harcourt				Sokoto			
	Min	**Max.**	**Mean**	**STD**	**Min**	**Max.**	**Mean**	**STD**	**Min**	**Max.**	**Mean**	**STD**
Jan.	3.28	5.50	1.63	0.83	0.49	2.34	1.05	0.37	2.79	6.14	4.38	0.74
Feb.	3.30	5.37	1.10	0.65	0.57	1.96	1.33	0.41	1.92	5.73	4.13	1.01
Mar.	1.32	5.54	1.20	0.45	1.12	1.92	1.68	0.19	1.17	5.19	2.93	1.02
Apr	0.17	4.80	1.92	0.38	1.39	1.91	1.71	0.13	0.80	4.44	1.76	0.77
May	0.32	4.12	1.76	0.29	1.42	1.98	1.66	0.14	1.55	4.43	3.06	0.75
Jun.	1.50	4.23	1.68	0.27	1.50	2.34	1.95	0.20	2.48	4.27	3.45	0.43
Jul.	2.42	4.16	1.94	0.31	1.86	2.63	2.27	0.16	2.36	3.64	2.98	0.35
Aug.	1.54	3.08	1.86	0.38	2.03	2.73	2.38	0.16	1.07	2.83	2.00	0.36

Sept.	1.05	2.62	1.07	0.20	1.70	2.44	2.07	0.18	0.79	2.40	1.52	0.40
Oct.	0.21	2.32	0.77	0.27	1.40	2.02	1.67	0.14	0.61	2.43	1.29	0.40
Nov.	2.18	4.11	1.27	0.55	0.59	1.64	1.19	0.26	1.94	4.34	3.10	0.60
Dec.	3.23	4.80	1.76	0.55	0.51	1.40	0.85	0.20	2.18	5.43	4.09	0.57

5. CONCLUSIONS

The application of wind speed prediction to energy production is of significant value, as wind power has a significant impact on the planning and stability of power energy around the world. This study demonstrates that different LSTM neural networks are used to optimize some hyper-parameters in the establishment of LSTM prediction models within the algorithm framework. When RMSE prediction is compared to certain empirical methods, it is discovered that some parameters and the double-layer LSTM of the wind speed dataset are extremely essential. In comparison to the impact of some neural networks and statistical model, the FWA-LSTM model produced some predictions in the generation of wind speed. However, the LSTM model of the wind speed experiment result showed that when compared to each other, that is, LSTM and FWA-LSTM methods, error in wind speed prediction was significantly reduced. As a result of the wind speed investigation, it was discovered that wind speed occurrence was more probable at stations like Damaturu, Sokoto, and Ikeja. This could result from the exposure of stations to tides and ocean currents.

As a result of this research, it was concluded that the investigation of wind speed energy using the improved active learning algorithm could be applied to the effective generalization of the larger validation of the data set, which would facilitate the prediction of wind energy optimization and its importance for power planning to reduce the pressure mounted on hydro energy generation because wind energy is also a renewable source of energy. Therefore, this research recommends that the government of the Federal Republic of Nigeria invest more funds in research to help solve Nigeria's power outage.

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7. DATA AVAILABILITY

The data used for this research were collected from the archive of the MERRA-2 website of Solar Data, (http://www.soda-pro.com).

NOMENCLATURE

ANN	Artificial Neural Network
Bi-LSTM	Bidirectional Long-Short Term Memory
CEEMDAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
CSV	Comma-Separated Value
FWA	Fire-Work Algorithms
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
MAE	Mean Average Error
MERRA-2	Modern-Era retrospective Analysis for Research and Applications, Version 2
MISOD	Multiple Single Output Data
MOMID	Multiple Outputs, Multiple Inputs Data
ML	Machine Learning
MLA	Machine Learning Algorithm
MSE	Mean Squared Error
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
R Square	Root Square
SISOD	Single, Single Output Data
SNAP	Sentinel Application Platform
VMD	Variational Mode Decomposition
WT	Wind Turbine

REFERENCES

1. Adebayo, S., Aweda, F.O., Ojedokun, I.A., & Olapade, O.T. (2022). Refractive index perception and prediction of radio wave through recursive neural networks using meteorological data parameters. *International Journal of Engineering, 35*(4), 810-818. https://doi.org/10.5829/IJE.2022.35.04A.21
2. Agbo, E.P., Edet, C.O., Magu, T.O., Njok, A.O., Ekpo, C.M., & Louis, H. (2021). Solar energy: A panacea for the electricity generation crisis in Nigeria. *Heliyon, 7*(5), e07016. https://doi.org/10.1016/j.heliyon.2021.e07016
3. Aliyu, A.S., Dada, J.O., & Adam, I.K. (2015). Current status and future prospects of renewable energy in Nigeria. *Renewable and Sustainable Energy Reviews, 48*, 336-346. https://doi.org/10.1016/j.rser.2015.03.098
4. Antor, A.F., & Wollega, E.D. (2020). *Comparison of machine learning algorithms for wind speed prediction.* Proceedings of the International Conference on Industrial Engineering and Operations Management. http://www.ieomsociety.org/detroit2020/papers/198.pdf
5. Asiegbu, A. (2007). Studies of wind resources in Umudike, South East Nigeria-An assessment of economic viability. https://medwelljournals.com/abstract/?doi=jeasci.2007.1539.1541
6. Aweda, F.O., Adebayo, S., Samson, T.K., & Ojedokun, I.A. (2021). Modelling net radiative measurement of meteorological parameters using merra-2 data in sub-sahara african town. *Iranian (Iranica) Journal of Energy & Environment, 12*(2), 173-180. https://doi.org/10.5829/IJEE.2021.12.02.10
7. Aweda, F.O., Olufemi, S.J., & Agbolade, J.O. (2022). Meteorological parameters study and temperature forecasting in selected stations in sub-sahara africa using merra-2 data. *Nigerian Journal of Technological Development, 19*(1), 80-91. https://doi.org/10.4314/njtd.v19i1.9
8. Aweda, F.O., Oyewole, J.A., Fashae, J.B., & Samson, T.K. (2020). Variation of the earth's irradiance over some selected towns in Nigeria. *Iranian (Iranica) Journal of Energy & Environment, 11*(4), 301-307. https://doi.org/10.5829/IJEE.2020.11.04.08
9. Brahimi, T., Alhebshi, F., Alnabilsi, H., Bensenouci, A., & Rahman, M. (2019). Prediction of wind speed distribution using artificial neural network: The case of saudi arabia. *Procedia Computer Science, 163*, 41-48. https://doi.org/10.1016/j.procs.2019.12.084
10. Chang, T.P. (2011a). Estimation of wind energy potential using different probability density functions. *Applied Energy, 88*(5), 1848-1856. https://doi.org/10.1016/j.apenergy.2010.11.010
11. Chang, T.P. (2011b). Performance comparison of six numerical methods in estimating weibull parameters for wind energy application. *Applied Energy, 88*(1), 272-282. https://doi.org/10.1016/j.apenergy.2010.06.018
12. Dhunny, A.Z., Lollchund, R.M., Boojhawon, R., & Rughooputh, S.D. (2014). Statistical modelling of wind speed data for mauritius. *International Journal of Renewable Energy Research. 4*(4), 1056-1064. https://doi.org/10.20508/ijrer.v4i4.1664.g6447
13. Gelaro, R., McCarty, W., Suárez, M.J., Todling, R., Molod, A., Takacs, L., Reichle, R. Wargan, K., Coy, L., Cullather, R., Draper, C., Akella, S., Buchard, V., Conaty, A., Silva, A.M.D., Gu, W., Kim, G.K., Koster, R., Lucchesi, R., Merkova, D., Nielsen, J.E., Partyka, G., Pawson, S., Putman, W., Rienecker, M., Schubert, S.D., Sienkiewicz, M., & Zhao,

B. (2017). The modern-era retrospective analysis for research and applications, version 2 (merra-2). *Journal of Climate, 30*(14), 5419-5454. https://doi.org/10.1175/JCLI-D-16-0758.1

14. Hassani, Z., Hajihashemi, V., Borna, K., & Sahraei Dehmajnoonie, I. (2020). A classification method for e-mail spam using a hybrid approach for feature selection optimization. *Journal of Sciences, Islamic Republic of Iran, 31*(2), 165-173. https://dx.doi.org/10.22059/JSCIENCES.2020.288729.1007444
15. Hosseini, E., Behzadfar, N., Hashemi, M., Moazzami, M., & Dehghani, M. (2022). Control of pitch angle in wind turbine based on doubly fed induction generator using fuzzy logic method. *Journal of Renewable Energy and Environment (JREE), 9*(2), 1-7. https://dx.doi.org/10.30501/JREE.2021.293546.1226
16. Junior, J.R.B., & do Carmo Nicoletti, M. (2019). An iterative boosting-based ensemble for streaming data classification. *Information Fusion, 45*, 66-78. https://doi.org/10.1016/j.inffus.2018.01.003
17. Justus, C., Hargraves, W., Mikhail, A., & Graber, D. (1978). Methods for estimating wind speed frequency distributions. *Journal of Applied Meteorology (1962-1982)*, *17*(3), 350-353. https://doi.org/10.1175/1520-0450(1978)017<0350:MFEWSF>2.0.CO;2
18. Kaoga, D.K., Raidandi, D., Djongyang, N., & Doka, S.Y. (2014). Comparison of five numerical methods for estimating weibull parameters for wind energy applications in the district of kousseri, cameroon. *Asian Journal of Natural & Applied Sciences, 3*(1), 72. http://www.ajsc.leena-luna.co.jp/AJSCPDFs/Vol.3%281%29/AJSC2014%283.1-08%29.pdf
19. Khosravi, A., Koury, R., Machado, L., & Pabon, J. (2018). Prediction of wind speed and wind direction using artificial neural network, support vector regression and adaptive neuro-fuzzy inference system. *Sustainable Energy Technologies and Assessments, 25*, 146-160. https://doi.org/10.1016/j.seta.2018.01.001
20. Lawan, S., Abidin, W., & Masri, T. (2020). Implementation of a topographic artificial neural network wind speed prediction model for assessing onshore wind power potential in Sibu, Sarawak. *The Egyptian Journal of Remote Sensing and Space Science, 23*(1), 21-34. https://doi.org/10.1016/j.ejrs.2019.08.003
21. Li, J., & Tan, Y. (2019). A comprehensive review of the fireworks algorithm. *ACM Computing Surveys (CSUR), 52*(6), 1-28. https://dl.acm.org/doi/fullHtml/10.1145/3362788
22. Lin, Z., Liu, X., & Collu, M. (2020). Wind power prediction based on high-frequency scada data along with isolation forest and deep learning neural networks. *International Journal of Electrical Power & Energy Systems, 118*, 105835. https://doi.org/10.1016/j.ijepes.2020.105835
23. Liu, X., Zhang, H., Kong, X., & Lee, K.Y. (2020). Wind speed forecasting using deep neural network with feature selection. *Neurocomputing, 397*, 393-403. https://doi.org/10.1016/j.neucom.2019.08.108
24. Ma, X., Chen, Y., Yi, W., & Wang, Z. (2021). Prediction of extreme wind speed for offshore wind farms considering parametrization of surface roughness. *Energies, 14*(4), 1033. https://dx.doi.org/10.3390/en14041033
25. Ma, Z., Chen, H., Wang, J., Yang, X., Yan, R., Jia, J., & Xu, W. (2020). Application of hybrid model based on double decomposition, error correction and deep learning in short-term wind speed prediction. *Energy Conversion and Management, 205*, 112345. https://doi.org/10.1016/j.enconman.2019.112345
26. Maheri, A., Wiratama, I.K., & Macquart, T. (2022). Performance of microtabs and trailing edge flaps in wind turbine power regulation: A numerical analysis using wtsim. *Journal of Renewable Energy and Environment (JREE), 9*(2), 18-26. https://dx.doi.org/10.30501/JREE.2021.291397.1220
27. Martin, M., Cremades, L., & Santabarbara, J. (1999). Analysis and modelling of time series of surface wind speed and direction. *International Journal of Climatology: A Journal of the Royal Meteorological Society, 19*(2), 197-209. https://doi.org/10.1002/(SICI)1097-0088(199902)19:2<197::AID-JOC360>3.0.CO;2-H
28. Memarzadeh, G., & Keynia, F. (2020). A new short-term wind speed forecasting method based on fine-tuned lstm neural network and optimal input sets. *Energy Conversion and Management, 213*, 112824. https://doi.org/10.1016/j.enconman.2020.112824
29. Mert, I., & Karakuş, C. (2015). A statistical analysis of wind speed data using burr, generalized gamma, and weibull distributions in Antakya, Turkey. *Turkish Journal of Electrical Engineering and Computer Sciences, 23*(6), 1571-1586. https://dx.doi.org/10.3906/elk-1402-66
30. Moghadasi, M., Ozgoli, H.A., & Farhani, F. (2021). Steam consumption prediction of a gas sweetening process with methyldiethanolamine solvent using machine learning approaches. *International Journal of Energy Research, 45*(1), 879-893. https://doi.org/10.1002/er.5979
31. Moreno, S.R., da Silva, R.G., Mariani, V.C., & dos Santos Coelho, L. (2020). Multi-step wind speed forecasting based on hybrid multi-stage decomposition model and long short-term memory neural network. *Energy Conversion and Management, 213*, 112869. https://doi.org/10.1016/j.enconman.2020.112869
32. Munteanu, I., Bratcu, A.I., CeangĂ, E., & Cutululis, N.-A. (2008). *Optimal Control of Wind Energy Systems: Towards a Global Approach* (Vol. 22). Springer. https://link.springer.com/book/10.1007/978-1-84800-080-3
33. Navas, R.K.B., Prakash, S., & Sasipraba, T. (2020). Artificial neural network based computing model for wind speed prediction: A case study of coimbatore, Tamil Nadu, India. *Physica A: Statistical Mechanics and its Applications, 542*, 123383. https://doi.org/10.1016/j.physa.2019.123383
34. Neshat, M., Nezhad, M.M., Mirjalili, S., Piras, G., & Garcia, D.A. (2022). Quaternion convolutional long short-term memory neural model with an adaptive decomposition method for wind speed forecasting: North aegean islands case studies. *Energy Conversion and Management, 259*, 115590. https://doi.org/10.1016/j.enconman.2022.115590
35. Nezhad, M.M., Heydari, A., Groppi, D., Cumo, F., & Garcia, D.A. (2020). Wind source potential assessment using sentinel 1 satellite and a new forecasting model based on machine learning: A case study Sardinia islands. *Renewable Energy, 155*, 212-224. https://doi.org/10.1016/j.renene.2020.03.148
36. Nezhad, M.M., Heydari, A., Neshat, M., Keynia, F., Piras, G., & Garcia, D.A. (2022). A mediterranean sea offshore wind classification using merra-2 and machine learning models. *Renewable Energy, 190*, 156-166. https://doi.org/10.1016/j.renene.2022.03.110
37. Nezhad, M.M., Neshat, M., Piras, G., & Garcia, D.A. (2022). Sites exploring prioritisation of offshore wind energy potential and mapping for wind farms installation: Iranian islands case studies. *Renewable and Sustainable Energy Reviews, 168*, 112791. https://doi.org/10.1016/j.rser.2022.112791
38. Nielson, J., Bhaganagar, K., Meka, R., & Alaeddini, A. (2020). Using atmospheric inputs for artificial neural networks to improve wind turbine power prediction. *Energy, 190*, 116273. https://doi.org/10.1016/j.energy.2019.116273
39. Ohunakin, O.S., & Akinnawonu, O.O. (2012). Assessment of wind energy potential and the economics of wind power generation in Jos, Plateau State, Nigeria. *Energy for Sustainable Development, 16*(1), 78-83. https://doi.org/10.1016/j.esd.2011.10.004
40. Olubi, O., Oniya, E., & Owolabi, T. (2021). Development of predictive model for radon-222 estimation in the atmosphere using stepwise regression and grid search based-random forest regression. *Journal of the Nigerian Society of Physical Sciences*, *3*(2), 132-139. https://doi.org/10.46481/jnsps.2021.177
41. Oyedepo, S.O. (2014). Towards achieving energy for sustainable development in Nigeria. *Renewable and Sustainable Energy Reviews, 34*, 255-272. https://doi.org/10.1016/j.rser.2014.03.019
42. Oyewole, J.A., Aweda, F.O., & Oni, D. (2019). Comparison of three numerical methods for estimating weibull parameters using Weibull distribution model in Nigeria. *Nigerian Journal of Basic and Applied Sciences, 27*(2), 8-15. https://doi.org/10.4314/njbas.v27i2.2
43. Pei, Y., Zheng, S., Tan, Y., & Takagi, H. (2012). *An empirical study on influence of approximation approaches on enhancing fireworks algorithm.* Proceedings of the 2012 IEEE International Conference on Systems, Man, and Cybernetics (SMC). https://doi.org/10.1109/ICSMC.2012.6377916
44. Pishgar-Komleh, S., Keyhani, A., & Sefeedpari, P. (2015). Wind speed and power density analysis based on Weibull and Rayleigh distributions (A case study: Firouzkooh county of Iran). *Renewable and Sustainable Energy Reviews, 42*, 313-322. https://doi.org/10.1016/j.rser.2014.10.028
45. Pobočíková, I., & Sedliačková, Z. (2014). Comparison of four methods for estimating the Weibull distribution parameters. *Applied Mathematical Sciences, 8*(83), 4137-4149 https://www.researchgate.net/publication/309918562_Comparison_of_Four_Methods_for_Estimating_the_Weibull_Distribution_Parameters

46. Rodríguez, F., Florez-Tapia, A.M., Fontán, L., & Galarza, A. (2020). Very short-term wind power density forecasting through artificial neural networks for microgrid control. *Renewable Energy, 145*, 1517-1527. https://doi.org/10.1016/j.renene.2019.07.067

47. Rojas, R. (2009). Adaboost and the super bowl of classifiers a tutorial introduction to adaptive boosting. *Technical Report of Freie University, Berlin.* https://www.inf.fu-berlin.de/inst/ag-ki/adaboost4.pdf

48. Salahaddin, A.A. (2013). Comparative study of four methods for estimating Weibull parameters for Halabja, Iraq. *International Journal of Physical Sciences, 8*(5), 186-192. https://doi.org/10.5897/IJPS12.697

49. Samadianfard, S., Hashemi, S., Kargar, K., Izadyar, M., Mostafaeipour, A., Mosavi, A., Nabipour, N., & Shamshirband, S. (2020). Wind speed prediction using a hybrid model of the multi-layer perceptron and whale optimization algorithm. *Energy Reports, 6*, 1147-1159. https://doi.org/10.1016/j.egyr.2020.05.001

50. Shao, B., Song, D., Bian, G., & Zhao, Y. (2021). Wind speed forecast based on the lstm neural network optimized by the firework algorithm. *Advances in Materials Science and Engineering, 2021.* https://doi.org/10.1155/2021/4874757

51. Staff, International Energy Agency. (2012). *Energy Balances of Non-OECD Countries*: Organization for Economic. https://doi.org/10.1787/energy_bal_non-oecd-2012-en

52. Tan, Y., & Zhu, Y. (2010). *Fireworks algorithm for optimization.* Part 1, Proceedings of the Advances in Swarm Intelligence: First International Conference, ICSI, Beijing, China. https://doi.org/10.1007/978-3-642-13495-1_44

53. Uçar, M.K., Nour, M., Sindi, H., & Polat, K. (2020). The effect of training and testing process on machine learning in biomedical datasets. *Mathematical Problems in Engineering, 2020.* https://doi.org/10.1155/2020/2836236

54. Venkatakrishnan, G., Rengaraj, R., Sathish, K., Dinesh, R., & Nishanth, T. (2021). Implementation of modified differential evolution algorithm for hybrid renewable energy system. *Journal of the Nigerian Society of Physical Sciences*, *3*(3), 209-215. https://doi.org/10.46481/jnsps.2021.240

55. Waewsak, J., Chancham, C., Landry, M., & Gagnon, Y. (2011). An analysis of wind speed distribution at Thasala, Nakhon Si Thammarat, Thailand. *Journal of Sustainable Energy & Environment, 2*(2), 51-55. https://www.thaiscience.info/Journals/Article/JOSE/10889661.pdf

56. Wang, C., Zhang, H., & Ma, P. (2020). Wind power forecasting based on singular spectrum analysis and a new hybrid laguerre neural network. *Applied Energy, 259*, 114139. https://doi.org/10.1016/j.apenergy.2019.114139)

57. Yin, W., Kann, K., Yu, M., & Schütze, H. (2017). Comparative study of CNN and RNN for natural language processing. https://arxiv.org/abs/1702.01923

58. Zafirakis, D., Tzanes, G., & Kaldellis, J.K. (2019). Forecasting of wind power generation with the use of artificial neural networks and support vector regression models. *Energy Procedia, 159*, 509-514. https://doi.org/10.1016/j.egypro.2018.12.007

59. Zhang, B., Zheng, Y.-J., Zhang, M.-X., & Chen, S.-Y. (2015). Fireworks algorithm with enhanced fireworks interaction. *IEEE/ACM Transactions on Computational Biology and Bioinformatics, 14*(1), 42-55. https://doi.org/10.1109/TCBB.2015.2446487

60. Zhang, Z., Qin, H., Liu, Y., Wang, Y., Yao, L., Li, Q., Li, J., & Pei, S. (2019). Long short-term memory network based on neighborhood gates for processing complex causality in wind speed prediction. *Energy Conversion and Management, 192*, 37-51. https://doi.org/10.1016/j.enconman.2019.04.006

61. Zheng, S., Janecek, A., & Tan, Y. (2013). *Enhanced fireworks algorithm.* Proceedings of the 2013 IEEE congress on evolutionary computation. https://ieeexplore.ieee.org/document/6557813