



Wind energy potential prediction of Bamenda, Cameroon based on artificial neural network models

Ghaila Bongyu Glory ^a, Joseph Ebobenow ^b, Marceline Motchongom Tingue ^c, David Afungchui ^{a,*}

^a Department of Physics, Faculty of Sciences, University of Bamenda, P.O Box 39, Bambili, Cameroon

^b Department of Physics, Faculty of Sciences, University of Buea, P.O Box 63, Buea, Cameroon

^c Department of Fundamental Sciences, Higher Technical Training College, University of Bamenda, P.O Box 39, Bambili, Cameroon

ARTICLE INFO

Article history:

Received September 12, 2025

Revised February 24, 2026

Accepted May 18, 2026

Available online May 19, 2026

Published May 24, 2026

Keywords:

Wind speed prediction,
Artificial Neural Networks,
Multilayer Perceptron,
Levenberg-Marquardt,
Feed-forward,
Back-propagation.

ABSTRACT

This study evaluates the performance of Artificial Neural Network (ANN) models for long-term monthly wind speed forecasting in Bamenda, Cameroon, a mid-altitude tropical region characterized by complex topography and challenging climatic conditions. Reliable long-term wind forecasting is essential for effective wind energy planning and sustainable renewable energy development, particularly in under-studied tropical regions. The research compares two ANN architectures, the Multilayer Perceptron (MLP) and the Nonlinear Autoregressive model with Exogenous Inputs (NARX), to determine which provides more accurate monthly wind speed predictions. Using 35 years of meteorological data (1979–2014), the study incorporates five input variables: relative humidity, precipitation, solar radiation, wind direction, and minimum and maximum temperatures. A rigorous sensitivity analysis was conducted to examine the effects of the activation functions, hidden layer neurons, input delays, and different training, validation, and testing data proportions on the model accuracy. The Levenberg–Marquardt training algorithm was applied, while model performance was assessed using statistical indicators such as the coefficient of determination (R^2), Mean Squared Error, Root Mean Squared Error, and Mean Absolute Percentage Error. Contrary to expectations favouring more complex temporal models, the simpler MLP architecture achieved superior predictive performance, with an overall R^2 value of 0.85255 compared to 0.71689 for the NARX model. The findings demonstrate that MLP models are computationally efficient and highly reliable for long-term wind energy assessment in Bamenda, thereby supporting renewable energy planning, environmental management, urban development, and Cameroon's efforts toward achieving the UN Sustainable Development Goals by 2030.

* Corresponding author, E-mail address: afungchui@yahoo.fr



1. INTRODUCTION

As time passes, the potential for global warming will increase due to the surge in the amount of greenhouse gases released into the atmosphere. According to Ripple et al. (2024), this phenomenon has accelerated in recent decades. The depletion of fossil reserves, increasing energy use, and the quest to preserve the environment from increasing pollution are some of the factors pushing humanity to alternative and cleaner sources of energy. Wind energy is an integral part of renewable energy, in addition to its role in mitigating environmental effects and weather forecasting. Temperature extremes and atmospheric pressure are examples of meteorological factors that can be used as input data into an artificial neural network (ANN) to accurately understand the wind energy level of the location of interest and its successful exploitation for the production of electrical energy. These factors are strongly related to the predominant wind patterns. A precise wind speed distribution calculation facilitates the control of atmospheric boundary layers and wind farm configuration. Numerous prediction techniques, including physical, statistical, intelligent, and hybrid approaches, are widely used in literature. The short-term forecast of the time sequence of observed wind speeds is better expressed using statistical techniques. However, it most often happens that wind speed patterns are both non-linear and unsteady, posing a challenge to the efficacy of this approach. While physical methods are better suited for estimating long-term time series of wind regimes, the required calculations remain highly intricate. Intelligent methods are notable for their resilience and online simulation capabilities, but they still show a merging rate that is sometimes reduced. The hybrid methods are robust, adopting a heuristic approach that leverages the strengths and experiences of the other approaches, but are also handicapped by increasing computational complexity.

Exploring the literature, we can summarize the occurrence of these approaches in what follows. A fuzzy model for wind speed prediction was trained using a genetic algorithm-based learning scheme, according to a method presented by Damousis et al. (2004). The multilayer perceptron (MLP) and support vector machines (SVM) were contrasted by Mohandes et al. (2004) for determining wind speed in Saudi Arabia. The mean monthly wind speed prediction for Turkey using the artificial neural network (ANN) was done by Bilgili et al. (2007). The prediction of wind power (WP) from wind farms (WF) in India using a neural network (NN) was done by Carolin Mabel & Fernandez (2008). To estimate wind speed, (Kulkarni et al., 2008) combined statistical methods such as curve fitting, periodic function extrapolation, the autoregressive integrated moving average model (ARIMA), and artificial neural networks (ANN). Monfared et al. (2009) demonstrated that accurate results could be achieved while lowering the number of neurons and training time by combining the ANN model with fuzzy logic. Salcedo-Sanz et al. (2009) created a hybrid model that combines the fifth-generation mesoscale model and artificial neural networks (ANN) for short-term (ST) predictions. For use in Portugal, another hybrid model created by Catalao et al. (2010) integrates particle swarm optimization with the wavelet transform. Ridgelet neural networks were employed by Amjady et al. (2011) for short-term wind power prediction. The authors demonstrated the method's ability to predict wind power output and a power system's total wind production. The ANN model was given preference over the ARIMA model for short-term wind speed prediction, according to Chen (2019). An evaluation of the autoregressive moving average (ARMA) and ANN models was conducted by De Giorgi et al. (2011). The least squares SVM and the seasonal autoregressive integrated moving average (SARIMA) were combined in a hybrid model by Guo et al. (2011b) for wind speed prediction in the Chinese Hexi Corridor. In comparison to the ARIMA-SVM, SARIMA, and ARIMA models, the authors showed that this hybrid model performed better. Neural network based on back-propagation (BP) was implemented by Guo et al. (2011a) for the wind speed prediction of Minqin, China. An attempt to integrate Bayesian algorithms (BA) models with the adaptive linear element (ADALINE), radial basis function (RBF), and back-propagation was done

by Li et al. (2022). It was demonstrated that Bayesian algorithms (BA) could be used to improve the regularity of the neural network. A hybrid model made up of a Markov chain and the ANN was established by Pourmousavi Kani & Ardehali (2011), who demonstrated that the hybridization mitigated prediction errors. Recurrent neural networks were compared with multivariate and univariate ARIMA models, portraying that the multivariate models were superior to the univariate variants, but the recurrent neural network produced more accurate results. Cassola & Burlando (2012) used the Kalman filter for the improvement of wind speed predictions. A revised feed-forward neural network (FNN) inspired by the empirical mode decomposition (EMD) was implemented by Guo et al. (2012), who found that the new model performed better in terms of accuracy than both the original EMD and the basic FNN model. Recent updates and formulation approaches in wind power generation prediction have been reported by Foley et al. (2012). An enhanced relevance vector machine (ORVM) approach was also presented by Yan et al. (2013), who established a probabilistic short-term and long-term wind power prediction technique based on a sparse Bayesian learning algorithm with ANN. This method was also used to predict the long-term wind speeds. The regression trees advancement method in predicting the short-term wind speed of Troncoso was documented by Azad et al. (2014). For the first time, Guo et al., (2011b) examined a deep learning method called the predictive deep Boltzmann machine that could perform over 10% better than the current techniques. An enhanced approach that employed RBF for the main forecasting and WT as a filter for the input data and based on wavelet transform (WT), hybrid neural networks, and imperialist competitive methodology was implemented by Aghajani et al. (2016). A neuro-fuzzy system with high predicting accuracy was examined by Saleh et al. (2016). A support vector regression-based methodology was developed by Santamaría-Bonfil et al. (2016) and contrasted with a few autoregressive techniques. It was demonstrated that the strategy outperformed the autoregressive approaches. Zhang et al. (2016) improved wind speed forecasting and produced successful prediction ranges by utilizing the autoregressive approach and Gaussian process regression (GPR). In a one- to three-step forecasting of wind speed, Xiao et al. (2017) demonstrated that the combination of singular spectrum analysis (SSA) and general regression neural networks produced accurate prediction results. Ahmed & Khalid (2018) showed that functional networks (FN) are a good way to predict wind speed in the short term. Aiming to estimate wind speed in India, Jamil & Zeeshan (2019) conducted a comparison study between an ANN and a disordered algorithm. Another method based on the combination of Elman NN (ELM), extreme learning machine (ELM), and long short-term memory (LSTM) neural network was also proposed by Chen & Lai (2011). Jiang et al. (2019) used the real-time enhanced variational decomposition model and conditional kernel density estimation to propose a complex probabilistic wind speed prediction method. For long-term wind speed prediction, SSA, EMD, Li et al. (2019) merged hybrid deep neural networks with turbulence intensity. In comparison to SVM, EMD-RBF, EMD-BP, EMD-Elman, and other methods, Mi et al. (2019) combined the convolutional SVM to estimate the wind speed profiles and WS predictions, and the model showed superior accuracy. The enhanced BP neural network and the wavelet transformation-Kullback–Leibler divergence, autoregressive fractionally integrated moving average were integrated by Wang & Li (2019) to estimate wind speed. Another hybrid model that considers the wind speed features in the accuracy of a multi-step calculation was recently proposed by Zhang et al. (2019).

Recently, Cai et al. (2020) proposed another high-performance algorithm, which is the reason artificial neural networks have demonstrated promising results when applied to most nonlinear and complex systems, making them a good choice to estimate wind speed.

In Cameroon, there is a problem in rural areas situated far from the electric distribution network, and electricity supply becomes problematic due to difficulty of accessibility and expense because of the cost of extending the electric network. However, due to its ease of use and adaptability to local conditions

through distributed production, renewable energy is currently undergoing a significant transition across the country (Šajn, 2016).

Currently, wind power development in Cameroon is lagging behind hydroelectric power, but the government is working towards diversifying energy sources and reducing fossil fuel dependency. As such, the country's first wind farm, a 10 MW project in the Northern region, was inaugurated in 2016 by ENEO and the Finnish company 'Win Wind'. The interest in renewable energy in Bamenda has been centered on solar power due to the city's hilly terrain, which makes it a reliable and cost-effective option for residents and businesses, especially in the sunny season marked by abundant insolation. Additionally, the city houses a 20 MW thermal plant located at Ntarikon, with 18 generators, 9 transformers, two 360 m³ water tanks that can autonomously meet 70% of the region's electrical power need in case the main transmission line fails. An accurate prediction of wind speed through the exploitation of meteorological data and advanced forecasting tools is essential for optimizing the installation of wind power in Bamenda. This study employs a rigorous comparative framework to assess whether the advanced temporal dynamics captured by the NARX model yields a measurable forecasting improvement over the simpler MLP architecture for monthly wind speed prediction. More specifically, this work focuses on long-term forecasting at a monthly resolution, which is critical for strategic energy planning, infrastructure development, and seasonal resource assessment, as opposed to short-term (hourly/daily) forecasting used for grid operation. The models are developed to estimate long-term wind energy yield from historical climate data, supporting site selection and preliminary feasibility assessments for wind power generation, rather than short-term operational forecasting.

Also, decision makers are guided to identify ideal turbine locations, ensuring maximum efficiency and significantly contributing to the energy supply of the city. Embracing wind energy as an alternative to fossil fuels can reduce the carbon footprint of Bamenda, curb climate change, and contribute to supporting the transition of Cameroon to cleaner energy and boosting its development goals. There is still a significant energy deficit marked by frequent power outages, even though solar power dominates Bamenda's renewable energy efforts due to its accessibility and abundant insolation. Wind energy is becoming more and more popular as a necessary supplement. Although wind power has been adopted more slowly than solar energy due to a number of issues, such as a lack of experience, limited equipment, and technological limitations, wind energy initiatives continue to advance, leading to a more sustainable and energy-independent future for Bamenda. The success of wind power projects is dependent on factors like a steady, directional, and powerful wind speed, which might not be easily accessible in all parts of Cameroon—the reason the region has been slow in adopting wind power. However, with increased awareness and potential business opportunities, there are chances for further funding and development of wind projects in Bamenda and Cameroon. Due to growing technological advancements and increased expertise in managing wind power projects, the region is likely to see a greater push toward wind energy adoption in the future. This will help it somewhat raise its human development index and meet the UN Sustainable Development Goals (SDGs) by 2030. Therefore, it is crucial to accurately predict the potential wind speed. The analysis will enable the prediction of Bamenda's average monthly wind speed, which is a determinant for the wind energy industry and a trustworthy indicator of the wind potential at a specific location. It is important to note that these methods have been applied in Bapouh's city in the West Region, which is a neighborhood of Bamenda, with satisfactory results (Talla Konchou et al., 2021).

The organization of the rest of the paper is as follows. In Section 2, we present wind speed data, and a few performance metrics are displayed in Section 3 of the methods. The outcomes are discussed in Section 4. In Section 5, the conclusions and perspectives are presented.

2. METHODS

The primary objective of this methodological framework was to conduct a controlled, definitive experiment to determine the optimal artificial neural network architecture for monthly wind speed and energy potential forecasting in Bamenda, Cameroon. This study specifically tested the hypothesis that the Nonlinear Autoregressive with Exogenous Inputs (NARX) model—with its inherent capacity to model temporal dynamics—would outperform the standard feedforward Multilayer Perceptron (MLP) for this time-series task. To ensure an impartial comparison, both models were applied to an identical dataset using the same preprocessing pipeline, validation protocol, and set of performance metrics. Plots have been generated in MATLAB R2024a using custom scripts developed for this study, while the figure itself is presented as an image in this paper. The following subsections detail the study site and data collection (2.1), feature engineering (2.2), temporal resolution and prediction task (2.3), multilayer perceptron (MLP) (2.4), and nonlinear autoregressive network with exogenous inputs (NARX) (2.5).

2.1 Study site and data collection

For thirty-five years, from January 1, 1979, to July 31, 2014, the data were gathered on a monthly basis and employed to characterize the long-term wind climatology and assess the wind energy potential at the Bamenda site. This extended period is essential to establish a reliable climatic baseline, capture decadal variability, and compute statistically robust estimates of wind power density for feasibility studies and energy system planning.

The data was sourced from <http://globalweathertamu.edu/>. Longitude, latitude, elevation, and five parameters—temperature (maximum and minimum), precipitation, wind speed, relative humidity, and solar radiation—were used. These data were derived from satellite-based reanalysis products, specifically the Climate Forecast System Reanalysis (CFSR), which was accessed through the Texas A&M University global weather data for SWAT models. All data are included in the file.

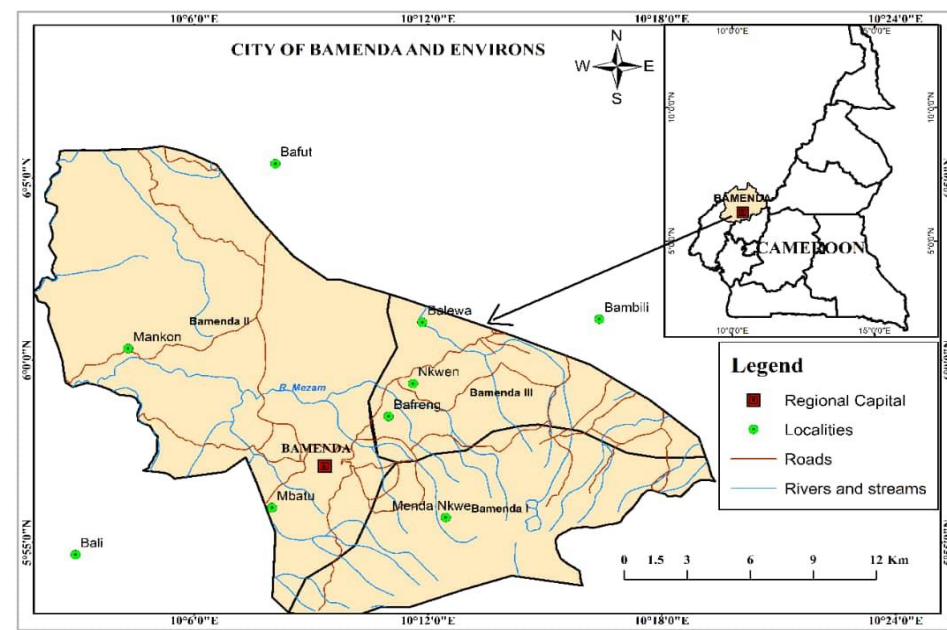


Fig 1. Localization of the site of Bamenda

2.1.1 Data sources, limitations and justification

The SWAT model's meteorological dataset was sourced via the Climate Forecast Reanalysis (CFSR) global dataset for a period of 1979–2014, refined by the Texas A&M University Global Weather service

(globalweather.tamu.edu). Being a reanalysis product, CFSR will likely show a divergence from actual ground measurements, especially in the Bamenda Highlands, which has a complex topography that makes local experimental systems sparse. Due to the lack of long-term local gauge data to carry out direct validation, the application of CFSR is affirmed and grounded in its use in regions of Africa having limited data challenges and complex topography, as documented in scientific literature. For instance, in the reference (Zhou et al., 2022), the WRF and satellite data were applied successfully. The model performed satisfactorily with a reduced RMSE, hence proving to be a reliable option. Similarly, the paper by Homa et al. (2025), successfully used SWAT model data from five gauging stations with data gaps such as groundwater abstraction and point sources, with promising results ($R^2 = 0.63$). Also, Ndhlovu & Woyessa (2021) applied gridded climatic data for hydrological modelling in data-scarce regions successfully, achieving results of $NS = 0.73$ and $R^2 = 0.73$, confirming this method to be a useful tool to estimate the main hydrological parameters and water resources. Likewise, Tulger Kara & ElbiR, (2024), successfully applied two reanalysis datasets: the fifth generation of the European Centre for Medium-Range Weather Forecast (ECMWF) atmospheric reanalysis of global climate (ERA5) and the modern-Era Retrospective analysis for Research and Applications, version-2 (MERRA2). As presented in their results, ERA5 had an R^2 range of 0.50–0.75 and MERRA-2 had an R^2 range of 0.33–0.62. These results offer valuable insights for selecting the most suitable dataset. This provides a stable, scientifically-rooted base for regional-scale analysis, though it doesn't eradicate uncertainties.

Therefore, the findings of this study are interpreted to indicate the wind energy potential within the Bamenda region. The results are dependent upon the performance of the CFSR dataset and stand for a step-by-step evaluation depending on the best accessible, spatially consistent atmospheric data. This work provides a baseline that future research can build upon using precise local data collection.

2.1.2 Data limitations and implications for wind energy applications

A crucial point in this study is the exploitation of monthly-averaged meteorological datasets in the methodology from the Climate Forecast System Reanalysis (CFSR). It is a major shortcoming for practical wind energy applications, which require higher temporal resolution – daily or hourly – as key (Fasel, 2025). Wind power generation exhibits great irregularity within synoptic and diurnal timescales caused by weather schemes and daily heating cycles. Due to the monthly-averaged data's nature, these critical variations are masked. Hence, though the use of a 35-year monthly dataset in this study is fitting for examining sustained seasonal rhythms and annual climate variations, its findings fall short of direct application to short-term predictions, in-depth turbine load analysis, or accurate financial calculations for particular wind projects (Huang et al., 2023). Unavailability of long-term, high-quality local measurement networks in the Bamenda highlands led to the choice of a global reanalysis product such as CFSR, sourced through the Texas A&M University Global Weather Service. Although reanalysis data is a suitable spatially and temporally option for foundational climatological studies, its irregularities are quite pronounced in regions of complex terrain like the hilly nature of Bamenda and cannot completely resolve local terrain-induced wind effects, giving rise to differences in wind speed and direction estimates at potential turbine sites.

In addition, exploration into the quality of reanalysis data for wind power reveals a robust diurnal cycle with poor performance at night (Rushdi et al., 2024). When data is collectively gathered to daily timescales, averaging data monthly makes it hard to extract precise, actionable insights.

Thus, findings of this study should be interpreted as one which offers a foundational evaluation of the Bamenda region's large-scale wind climate and long-term resource viability. Though establishing an essential scientific basis, translating this potential into specific projects will require future work to prioritize high-resolution, site-specific data for detailed engineering and operational planning.

2.2 Feature Engineering

Feature engineering is the process of creating valuable characteristics that will improve the prediction of a target in an effort to create a model having higher performance. A variety of strategies are used in this process, some of which have been applied to the dataset in question. Generally, a wind speed dataset's features are displayed at different scales. To guarantee that all figures are on the same scale and to provide homogeneity to the data collection, a Min-Max scale is used to translate each figure to the 0–1 range. This process also eliminates noise from the data. The learning process of the model is streamlined, and normalized input data is used in the prediction method to improve the effectiveness of error propagation in the process. Eq. (1) is used to normalize the data (Saleh et al., 2016):

$$Y_{scaled} = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \quad (1)$$

Where Y_{scaled} stands as the new scaled variable, Y is the initial value of the variable from the data, Y_{min} and Y_{max} are the highest and lowest values of the relevant variables in the data. As a result, Y_{scaled} is 1 when it is greatest and 0 when it is lowest. The normalized data set is segmented into three parts as per the default setting of the Neural Net Fitting Tool (NF) used. Out of 12988 samples, 70% (9091 samples) are used for training the neural network, 15% (1948 samples) for validation, and 15% (1948 samples) for testing the network. The 70-15-15 data partitioning scheme ensures the model is neither overfitted to the training data nor underdeveloped, as confirmed by its performance on the independent validation subset (15% of data). All tuning and feature analysis was done on the 70% training set. The primary utility of this model is to provide spatially continuous estimates of wind energy potential across the study area, effectively filling in data for locations without ground measurements by leveraging the learned regional climatic correlations. Multi-layer Perceptron and Nonlinear Autoregressive models with Exogenous Inputs are the two methods considered in this study to predict wind speed.

2.3 Temporal resolution and prediction task

Monthly averages were calculated for all meteorological variables, including wind speed, temperature, solar radiation, etc. This aggregation enabled the development and validation of MLP and NARX models for long-term trend forecasting. Specifically configured for one-step-ahead monthly predictions, these models serve as a tool for projecting seasonal and annual energy yield.

2.4 Multi-layer perceptron (MLP)

A Multi-layer Perceptron (MLP) is a variant of the neural network that operates in a feedforward manner, meaning that it is structured into groups of uniform neurons that are not interconnected, and data flows in one direction through its layers such that vector transformations are performed by receiving an input vector and converting it into an output vector. This network includes at least two layers: a hidden layer and an output layer, where at least one of these layers is non-linear and each layer only uses the outputs from the preceding layers, as reported by Velo et al. (2014).

A neuron in an MLP is defined by its activation function T and the number of inputs n , and computes the following function:

$$f(x_1, \dots, x_n) = T\left(\sum_{i=1}^n w_i x_i + t\right) \quad (2)$$

Where $f(x_1, \dots, x_n)$ is the function's output, $x_1, \dots, x_n$ are its input variables, T is the activation function that converts the weighted sum of the inputs and the bias in a non-linear way, and w_i are the weights

assigned to each input. Each input is multiplied by a corresponding weight, t is the bias term added to the weighted sum of the inputs before applying the activation function. The following two equations illustrate the alternative expressions that the function T can accept:

$$T(x) = \tanh(x) \quad (3)$$

$$T(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

Equation (2) assumes a unique form in a two layers case of MLP given as:

$$f(x) = \sum_k (w_{k1} \sum_j (w_{jk} + w_{0k}) + w_{01}) \quad (5)$$

Where f is the output of the function, which depends on the input variables x , w_{jk} are the weights connecting the hidden nodes to the output node, w_{jk} are the weights connecting the input variables to the hidden nodes, w_{0k} are the bias terms added to the sums within the inner summation, w_{01} is the bias term added to the outer summation. Equation (5) effectively depicts a multi-layer perceptron (MLP) structure in which the final output is obtained by aggregating the inputs through multiple layers, adding biases, and then weighting and summing the inputs. It captures the complexity of the connections between the input, the hidden, and the output layers in the neural network.

Three main stages are involved in implementing the neural network: the training, the validation, and the testing, mandating the dataset to be divided accordingly for each stage. During the training phase, training data is used to optimize the weights that define the network architecture, while in the validation phase, validation data helps fine-tune hyperparameters and optimize the model. Using test data, the testing phase assesses the neural network architecture's performance (Hinton et al., 2012). As a default, the data is split into three parts to train, validate, and test it in the ratio (75:15:15) (NG, 2017). The process of finding the correct weights is essentially a minimization problem where the error between the output of the network and the actual target value is minimized as shown in the following equation:

$$\operatorname{argmin}\{E_r\} = \operatorname{argmin}\left\{\sum_{i=1}^n (y_i - f_i)^2\right\} \quad (6)$$

Where *argmin* is the argument of the minimum, which represents the value of the parameter that minimizes the function, E_r , E_r denotes the error function being minimized, where n is the total number of data points, y_i are the actual target values (true values) from the dataset, and f_i are the model's predictions. In effect, Eq. (6) is minimizing the sum of squared errors between the actual target values y_i and the predicted values f_i , which is a common objective in regression problems to find the best fit for the model.

The following formula shows how a single neuron in an MLP functions:

$$z_i = \sum_{j=1} w_{ij} x_j + b_i \quad (7)$$

Here z_i is the output of the i^{th} node in the current layer and b_i is the bias term associated with the i^{th} node.

2.5 Nonlinear autoregressive network with exogenous inputs (NARX)

The NARX operates as a discrete-time nonlinear system. In this neural network model, the predicted value $\hat{s}(k+1)$ of the output at the $(k+1)^{\text{th}}$ step can be represented in two formulations:

$$\hat{s}(k+1) = G(\hat{s}(k), \dots, \hat{s}(k-q+1), r(k), \dots, r(k-q+1)) \quad (8)$$

$$\hat{w}(k+1) = G(s(k), \dots, s(k-q+1), r(k), \dots, r(k-q+1)) \quad (9)$$

where, the nonlinear function G maps the three quantities to the output ($\hat{s}(k+1)$); these are, the input sequence $(r(k), \dots, r(k-q+1))$, the predicted output sequence $(\hat{s}(k), \dots, \hat{s}(k-q+1))$, and the actual output sequence of values $(s(k), \dots, s(k-q+1))$.

- $r(k), \dots, r(k-q+1)$ is the input sequence from time steps k to $(k-q+1)$.
- $\hat{s}(k+1)$ is the predicted value of the output at the time step $(k+1)$.
- $\hat{s}(k), \dots, \hat{s}(k-q+1)$ are the predicted output values from time steps, k to $(k-q+1)$.
- $s(k), \dots, s(k-q+1)$ are the actual output values from time steps k to $(k-q+1)$.

In effect, these equations are part of the NARX (Nonlinear Autoregressive Network with Exogenous Inputs) model. They describe how the predicted output at the next time step is a function of both past predicted (or actual) output values and past input values. The temporal dependencies and behavioral effects of exogenous inputs are captured by this modeling approach.

3. PERFORMANCE EVALUATION OF THE MODELS

To evaluate the predicting accuracy of the models, various error measures on the test set were estimated by making a comparison between the actual and predicted values from the database. In this regard, the Mean Absolute Percent Error (MAPE), the Mean Absolute Error (MAE), and the Root Mean Square Error (RMSE) were the performance metrics considered and are expressed in Eqs. (10–12). Where n is the number of data points, and are the estimated and observed wind speeds, respectively. Details about the forecasting models' short-term efficiency are provided by RMSE, as expressed by Eq. (10), and it is intended to be negligibly close to zero and positive (Ceylan et al., 2017).

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - x_i)^2} \quad (10)$$

The mean absolute error (MAE) measures how well a model is performing and is best when it is near zero. It offers insight into the predictive performance of the model over time and is determined using Eq. (11) (Hinton et al., 2012).

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - x_i| \quad (11)$$

The MAPE measures the proportion of the actual value of the data in absolute terms to the mean of the absolute prediction errors. Greater accuracy demands smaller values of the MAPE (Ceylan et al., 2017). It is expressed as:

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{x_i - y_i}{x_i} \right| \quad (12)$$

The prediction of the model's level of success is classified as follows (Ağbulut et al., 2021): for high predictive accuracy, MAPE is strictly less than 0.1; for good forecasting, MAPE is between 0.1 and 0.2; and for inaccurate forecasting, MAPE is strictly greater than 0.5. The ANN regression functional approximation can be expressed as:

$$y = Wx + b \quad (13)$$

Where y represents the output, x is the input, W is the weight matrix, and b is the bias term. During training, W and b are adjusted to define the relationship between the input and output values. The form of the regression function depends on the architecture of the ANN, the parameters, and the training data.

4. RESULTS AND DISCUSSIONS

4.1 Feature assessment

Here, the model's predicted wind speed output was used to estimate the wind potential of Bamenda. The first step was the statistical study of data, followed by the prediction of the maximum wind speed using multi-layer perceptron (MLP) and non-linear autoregressive exogenous (NARX) input artificial neural network models.

Feature assessment consists of identifying the weather parameters that are suitable for the prediction of wind speed in the area of interest. Here, we carry out three tests on the data that will enable us to select the parameters of interest. The three tests include correlation analysis, study of the variance inflation factor, study of the P-values, and an analysis of variance (ANOVA) test.

4.1.1 Correlation analysis

The correlation between the variables is displayed in Table 1. The aim here is twofold: to check for multicollinearity and also to identify parameters that negatively impact wind speed. We observe that the correlation coefficient between temperature and shortwave irradiation is quite high, suggesting multicollinearity, but further investigation will be necessary before a valid conclusion can be made. It can also be noted that relative humidity, wind direction, and the amount of rainfall impact wind speed negatively, while the rest of the parameters influence it positively.

Correlation analysis indicates moderate pairwise associations with wind speed, particularly with solar radiation ($\max |r| = 0.49$). Regardless of these comparatively weaker correlations with other meteorological parameters, wind speed showed the highest predictive potential for estimating energy yield. Solar irradiance and ambient temperature were also identified as strong, correlative forecasters, while atmospheric pressure and relative humidity provided more moderate, yet visible, contributions to the model.

4.1.2 Variance inflation factor (VIF)

Table 2 presents a number of relevant regression indicators, of which interest will be directed to the VIF and the P-value. In general, the VIF can be summarized into three intervals as follows: either the VIF is less than 5, in which case it is accepted; or it lies between 5 and 10, in which case it demonstrates mild multicollinearity; or it is greater than 10, in which case there is strong multicollinearity and the parameter

can be rejected. From the values in Table 2, temperature, relative humidity, and short wave irradiation show some mild multicollinearity in each case, which is acceptable. In addition, the P-values being all far less than 0.05 are significant for all the parameters. The t-statistic (t-stat) for each variable's estimated coefficient, which assesses its statistical significance, was equally done.

Table 1. Correlation between variables

	T(K)	RH (%)	P (hPa)	V (m/s)	Wind direction (deg)	Rainfall (kg/m ²)	Short-wave irradiation (Wh/m ²)
T(K)	1	-0.72174	-0.2973	0.26008	-0.18678	-0.1455	0.808254
RH (%)	-0.72174	1	0.276533	-0.31042	0.410601	0.318793	-0.7335
P (hPa)	-0.2973	0.276533	1	0.059129	0.134881	0.05844	-0.05897
V (m/s)	0.26008	-0.31042	0.059129	1	-0.09684	-0.00716	0.493799
Wind direction (deg)	-0.18678	0.410601	0.134881	-0.09684	1	0.189009	-0.26731
Rainfall (kg/m ²)	-0.1455	0.318793	0.05844	-0.00716	0.189009	1	-0.18904
Short-wave irradiation (J/m ²)	0.808254	-0.7335	-0.05897	0.493799	-0.26731	-0.18904	1

Table 2. Regression indicators: Correlation coefficients, t-statistic, P-values, and Variance Inflation Factor (VIF), among others, for each variable.

	Coefficients	t-stat	P-value	VIF
T(K)	-0.14625	-164.27	0	3.847378
RH (%)	-0.00406	-27.3962	4.5E-165	3.099276
P (hPa)	-0.01242	-11.8716	1.69E-32	1.309066
Wind direction (deg)	0.000561	35.52456	6.2E-276	1.255728
Rainfall (kg/m ²)	0.047574	66.61139	0	1.134639
Short-wave irradiation (J/m ²)	8.87E-07	304.3794	0	3.950618

The analysis of variance (ANOVA) test is used to ascertain the statistical significance of a number of variables by comparing their means to determine if there are any significant differences. We observe in Table 2 that each weather parameter is statistically significant in predicting wind speed based on the P-values.

4.2 Neural network results and comparative forecasting performance

Table 1 displays the correlation coefficients between meteorological parameters and wind speed. The following—relative humidity, wind direction, and rainfall—show negative correlations, while other variables show positive correlations with wind speed. Temperature and short-wave irradiation exhibit higher correlation coefficients, which is an indication of potential multiple regression. Table 2 is a summary of regression indicators; variance inflation factor (VIF) values show moderate multiple regression for temperature, relative humidity, and short-wave irradiation, all within the acceptable range. In addition, the t-statistic (t-stat) for each variable's estimated coefficient, which assesses its statistical significance, was performed, and the P-values (<0.05) align with statistical significance for all variables,

underscoring their relevancy in wind speed forecasting. These results stress the importance of proper variable selection for Neural Network modelling. Parameter combinations tested in Table 3 and Table 4 were led by the differential correlation with maximum wind speed of relative humidity, pressure, precipitation, and wind direction.

Prediction precision gets better as the number of input parameters increases, as anticipated. By making use of multilayer perceptron (MLP) and nonlinear autoregressive with exogenous input (NARX) models, six different combinations of meteorological inputs were examined. Tables 5 and 6 tested the influence of activation functions, indicating that the hyperbolic tangent sigmoid (Tansig) and linear (Purelin) functions performed better, as indicated by their RMSE, MSE, and MAE values. In addition, Tables 7 and 8 show that a delay of four and an architecture made of ten hidden neurons, respectively, yields maximum results.

The higher R^2 values according to Table 3 and Table 4 (0.96639 for MLP, Combination 3; 0.93894 for NARX, Combination 2) refer to the most superior-performing input combinations discovered during the training/validation phase. A comparison of observed and actual wind speeds for the MLP and NARX models across training, validation, and testing datasets including the independent test set is presented in Figures 2 and 3. These plots detail the correlation strength and error distribution, with the NARX model exhibiting a closer fit to observed values. In addition, Figure 4 displays a time series fit of predicted and observed wind speed across the test dataset, clearly illustrating how model accuracy varies over time. The maximum MLP network gets correlation coefficients of 0.85421, 0.85798, 0.8387, and 0.85255, respectively, performing better than the NARX model, which records values of 0.72099, 0.71079, 0.7048, and 0.71689. These results show the topnotch predictive potential of the MLP model for wind speed in Bamenda.

Ultimately, the combination of wind direction, maximum pressure, maximum relative humidity, and time as input parameters achieves the most accurate predictions when evaluated with Tansig and Purelin activation functions, as shown in Figure 4. Generally, the incorporated synthesis of correlation, regression indicators, and neural network performance metrics demonstrates that the MLP model, optimized with ten neurons, a delay of four, and proper activation functions, yields dependable forecasts of wind speed and is highly feasible for real-world use.

4.3 Discussion of the MLP versus NARX Results using Monthly Meteorological Data

Tables 3 and 4 indicate that the MLP outperformed the NARX network for monthly wind prediction. The MLP has a simpler but efficient model, which is capable of capturing difficult, stable non-linearities, which agrees with this research task. It is able to recognize relationships between input variables and the output without complications or overfitting due to the temporal features and resolution of the dataset. Meanwhile, the NARX design structures, which are known to be theoretically robust for dynamic system modeling on short-term temporal dependencies, are weakened in the context of monthly resolution. Hence, the wind prediction problem changes from sequence modeling to pattern recognition established on seasonal and inter-annual signals.

Table 3, the NARX model performed better due to its inbuilt memory through feedback connections, this permits it to model with accuracy temporal dependencies in the wind series which is suitable to capture inertial and lagged effects in the dataset. Thus, combination 6, which consists of time-lagged variables (Temperature, Relative Humidity, Pressure, Wind Direction), is the most efficient.

Table 4, the MLP outperformed with a variable combination 4 (Temperature, Wind Speed, Precipitation, Pressure), showing its strength as a universal function approximator for static, non-linear relationships.

Its feedforward structure enables it to map the simultaneous input variables to the output in the absence of definite temporal feedback, which is an advantage for certain patterns in the data.

Table 3. Influence of the input variables on the prediction performance using the NARX Model

Input Variable	Combination Number	MSE	MAE	RMSE	R ²
WS, T	1	0.0154	0.14758	0.03924	0.85121
RH, P, WD	2	0.0132	0.13663	0.11528	0.93894
WS, T, P	3	0.0135	0.13817	0.11619	0.84903
WS, P, PRE	4	0.0138	0.13970	0.37148	0.86346
T, RH, WD	5	0.0206	0.19395	0.14374	0.89327
T, RH, PRE, WD	6	0.0128	0.134795	0.35844	0.91769

Table 4. Influence of the input variables on the prediction performance using MLP Model

Input Variable	Combination Number	MSE	MAE	RMSE	R ²
WS, T	1	0.0077	0.056811	0.08803	0.77278
RH, P, WD	2	0.0091	0.08345	0.09555	0.84750
WS, T, P	3	0.0097	0.06759	0.09849	0.96639
T, WS, P, PRE	4	0.0076	0.05862	0.08736	0.76692
T, RH, WD	5	0.0086	0.47760	0.09270	0.81346
T, RH, PRE, WD	6	0.0076	0.05504	0.08710	0.92538

The following sensitivity analysis to determine the optimal model parameters was conducted using only the training data.

Table 5. Influence of activation function on the prediction performance for the MLP

Activation Function	MSE	RMSE	MAE	R ²
Tansig-Purelin	0.0154	0.0392	0.1476	0.8798
Purelin-Tansig	0.0180	0.0896	0.2021	0.6326
Tansig-Logsig	0.1259	0.3548	0.4212	0.5297
Logsig-Tansig	0.1428	0.1050	0.1635	0.8668

Table 6. Influence of activation function on the prediction performance for the NARX

Activation Function	MSE	RMSE	MAE	R ²
Tansig-Purelin	0.0451	0.0672	0.2759	0.9659
Purelin-Tansig	0.0180	0.0896	0.2021	0.7328
Tansig-Logsig	0.1247	0.2679	0.5357	0.7297
Logsig-Tansig	0.1318	0.1050	0.1748	0.9684

Table 7. Influence of the number of delays at the input for the NARX

Number of delays	MSE	RMSE	MAE	R ²
02	0.01204	0.10973	0.1305	0.97997
04	0.01257	0.11212	0.15855	0.89999
06	0.012723	0.11279	0.15952	0.91168

Table 8. Influence of the number of neurons in the hidden layer for the MLP model

Number of neurons	MSE	RMSE	MAE	R ²
5	0.0127	0.015	0.0105	0.81134
10	0.0104	0.101	0.5	0.9012
20	0.0103	0.105	0.0105	0.99519

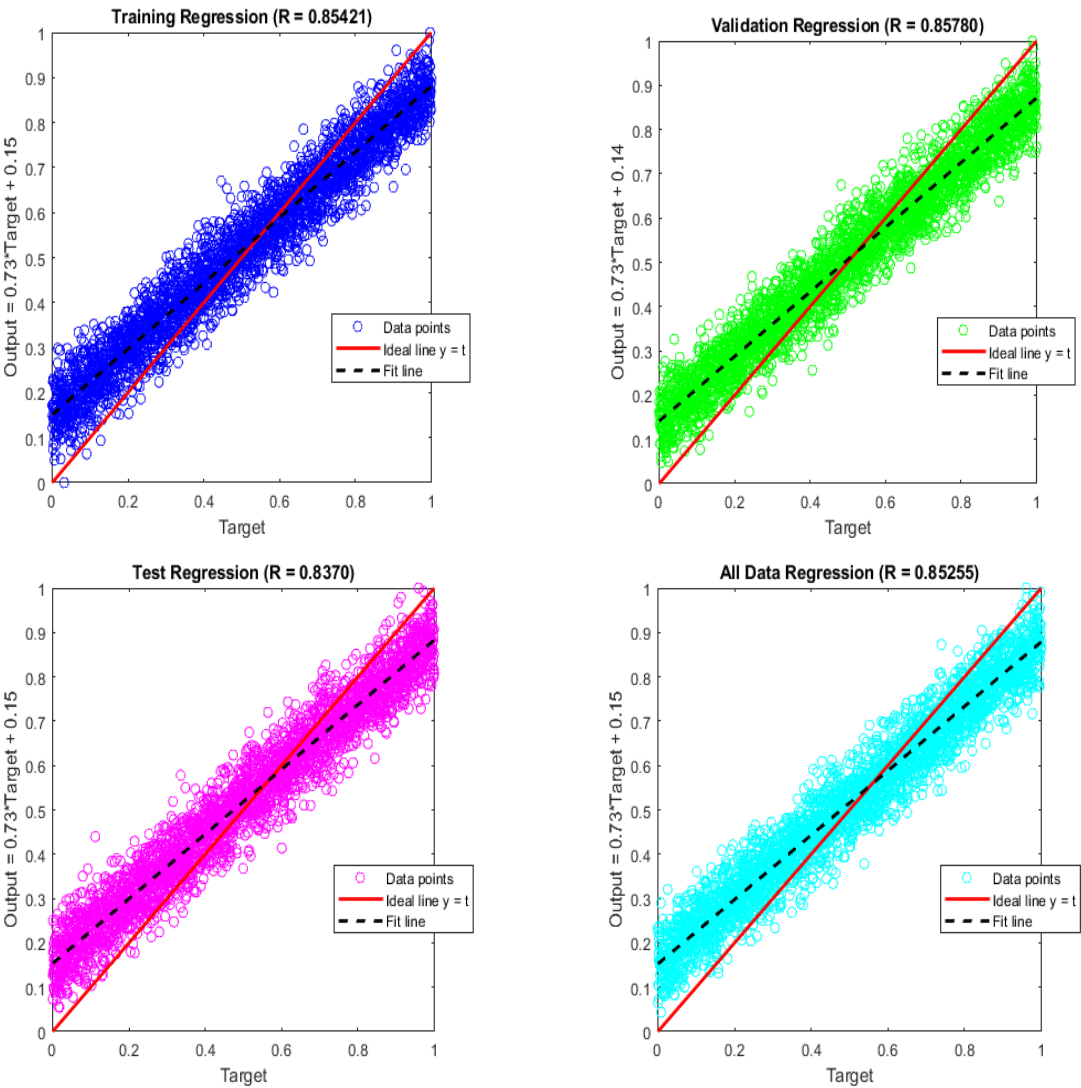


Fig 2. Regression plot of predicted versus observed wind speed using the **MLP model**, showing correlation strength and error distribution.

The plot of the measured and predicted wind speeds for the year 1979 against time in days for December is presented for an independent assessment of the network, as shown below. We observe a good fit between predictions and measurements, especially when the MLP is employed.

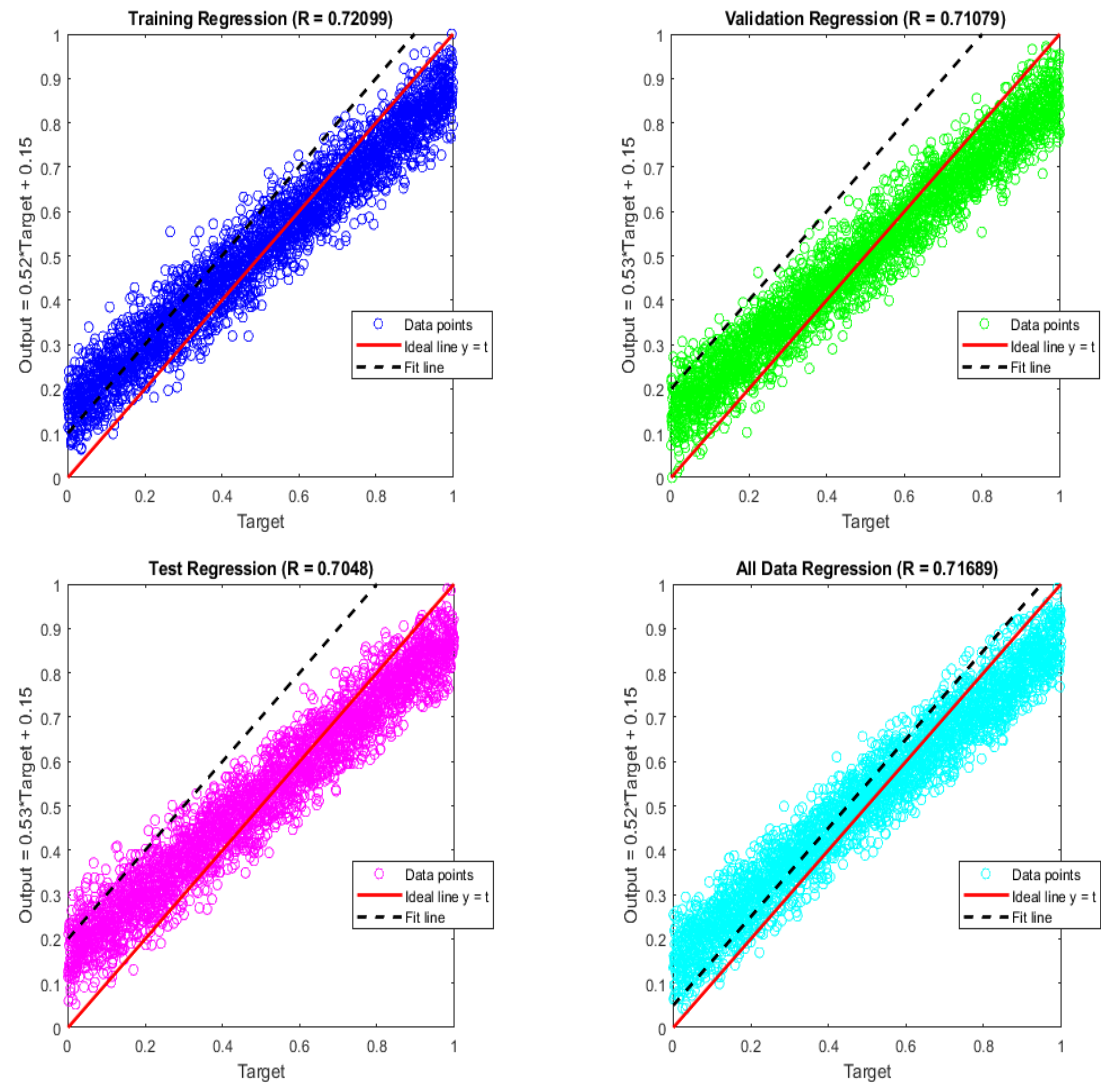


Fig 3. Regression plot of predicted versus observed wind speed using the **NARX model**, highlighting improved fit compared to MLP.

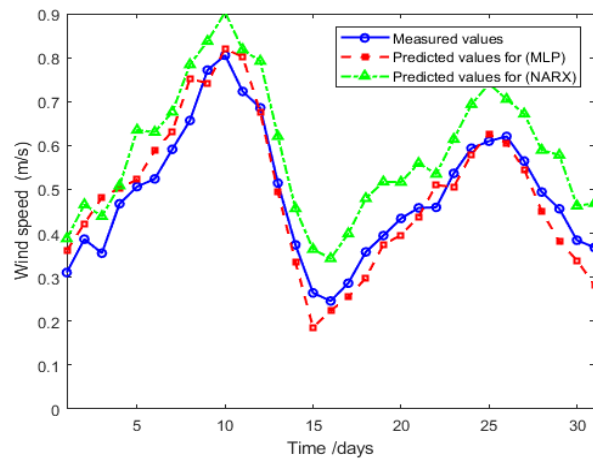


Fig 4. Measured versus predicted normalized wind speed (u/u_{max}) against time for the month of December.

5. CONCLUSION

The results of this study demonstrate how well artificial neural networks are suited for monthly wind speed forecasting in the Bamenda Highlands. Higher R^2 values were observed during training (up to 0.966 for MLP and 0.939 for NARX). The optimum models demonstrated robust generalization, with MLP (R^2 value of 0.85255) performing better than NARX (R^2 value of 0.71689), proving that MLP is more efficient. This is a relevant finding which can guide model selection based on data, an indication that simpler feedforward networks can be best for long-term trend forecasting in similar mid-altitude tropical climates, which can decrease computational cost for planners. The proposed model was calibrated for the Bamenda region, but the transferability of the ANN model to other geographic locations is contingent upon climatic and topographic similarity. The model can be directly applied in a new region within a similar climatic zone, using the same source of input reanalysis data (e.g., CFSR) for the new coordinates. Meanwhile, for regions with fundamentally different driving meteorological patterns, the model architecture could be retrained, but would require retraining on representative data from the target region to establish accurate local correlations. The principal limitation of this study stems from the model's reliance on the quality and spatial resolution of the input reanalysis data. Future work can validate the model with higher-frequency data to conceptualize near-term prediction merged with geographical information systems (GIS) for spatial resource mapping. Finally, this work provides a valid, AI-powered tool that contributes directly to accurate wind energy yield estimation, encouraging informed investment and policy for sustainable development in Cameroon and enabling the country to meet its UN sustainable development goals (SDGs).

REFERENCES

- Ağbulut, Ü., Gürel, A. E., & Biçen, Y. (2021). Prediction of daily global solar radiation using different machine learning algorithms: Evaluation and comparison. *Renewable and Sustainable Energy Reviews*, 135, 110114. <https://doi.org/10.1016/j.rser.2020.110114>.
- Aghajani, A., Kazemzadeh, R., & Ebrahimi, A. (2016). A novel hybrid approach for predicting wind farm power production based on wavelet transform, hybrid neural networks and imperialist competitive algorithm. *Energy Conversion and Management*, 121, 232–240. <https://doi.org/10.1016/j.enconman.2016.05.024>.
- Ahmed, A., & Khalid, M. (2018). An intelligent framework for short-term multi-step wind speed forecasting based on Functional Networks. *Applied Energy*, 225, 902–911. <https://doi.org/10.1016/j.apenergy.2018.04.101>.
- Amjady, N., Keynia, F., & Zareipour, H. (2011). Short-term wind power forecasting using ridgelet neural network. *Electric Power Systems Research*, 81(12), 2099–2107. <https://doi.org/10.1016/j.epsr.2011.08.007>.
- Azad, H. B., Mekhilef, S., & Ganapathy, V. G. (2014). Long-Term Wind Speed Forecasting and General Pattern Recognition Using Neural Networks. *IEEE Transactions on Sustainable Energy*, 5(2), 546–553. <https://doi.org/10.1109/TSTE.2014.2300150>.
- Bilgili, M., Sahin, B., & Yasar, A. (2007). Application of artificial neural networks for the wind speed prediction of target station using reference stations data. *Renewable Energy*, 32(14), 2350–2360. <https://doi.org/10.1016/j.renene.2006.12.001>.
- Cai, H., Jia, X., Feng, J., Li, W., Hsu, Y.-M., & Lee, J. (2020). Gaussian process regression for numerical wind speed prediction enhancement. *Renewable Energy*, 146, 2112–2123. <https://doi.org/10.1016/j.renene.2019.08.018>.

- Carolin Mabel, M., & Fernandez, E. (2008). Analysis of wind power generation and prediction using ANN: A case study. *Renewable Energy*, 33(5), 986–992. <https://doi.org/10.1016/j.renene.2007.06.013>.
- Cassola, F., & Burlando, M. (2012). Wind speed and wind energy forecast through Kalman filtering of Numerical Weather Prediction model output. *Applied Energy*, 99, 154–166. <https://doi.org/10.1016/j.apenergy.2012.03.054>.
- Catalao, J. P. S., Pousinho, H. M. I., & Mendes, V. M. F. (2010). Hybrid Wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal. *IEEE Transactions on Sustainable Energy*, 2(1), 50–59. <https://doi.org/10.1109/TSTE.2010.2076359>.
- Ceylan, İ., Gürel, A. E., & Ergün, A. (2017). The mathematical modeling of concentrated photovoltaic module temperature. *International Journal of Hydrogen Energy*, 42(31), 19641–19653. <https://doi.org/10.1016/j.ijhydene.2017.06.004>.
- Chen, L., & Lai, X. (2011). Comparison between ARIMA and ANN Models used in short-term wind speed forecasting. In *Proceedings of the 2011 Asia-Pacific Power and Energy Engineering Conference (APPEEC '11)*. IEEE Computer Society, USA, 1–4. <https://doi.org/10.1109/APPEEC.2011.5748446>.
- Chen, L. X. (2019). Organic solar cells: Recent progress and challenges. *ACS Energy Letters*, 4(10), 2537–2539. <https://doi.org/10.1021/acsenergylett.9b02071>.
- Damousis, I. G., Alexiadis, M. C., Theocharis, J. B., & Dokopoulos, P. S. (2004). A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation. *IEEE Transactions on Energy Conversion*, 19(2), 352–361. <https://doi.org/10.1109/TEC.2003.821865>.
- De Giorgi, M. G., Ficarella, A., & Tarantino, M. (2011). Error analysis of short term wind power prediction models. *Applied Energy*, 88(4), 1298–1311. <https://doi.org/10.1016/j.apenergy.2010.10.035>.
- Fasel, K. K. M. (2025). *Machine learning applications for wind resource mapping in Ajman, UAE: towards sustainable energy solutions*, PhD thesis, University of Greater Manchester. <https://ub-ir.bolton.ac.uk/esploro/outputs/doctoral/Machine-learning-applications-for--wind/9949533008841>.
- Foley, A. M., Leahy, P. G., Marvuglia, A., & McKeogh, E. J. (2012). Current methods and advances in forecasting of wind power generation. *Renewable Energy*, 37(1), 1–8. <https://doi.org/10.1016/j.renene.2011.05.033>.
- Guo, Z., Wu, J., Lu, H., & Wang, J. (2011a). A case study on a hybrid wind speed forecasting method using BP neural network. *Knowledge-Based Systems*, 24(7), 1048–1056. <https://doi.org/10.1016/j.knosys.2011.04.019>.
- Guo, Z., Zhao, J., Zhang, W., & Wang, J. (2011b). A corrected hybrid approach for wind speed prediction in Hexi Corridor of China. *Energy*, 36(3), 1668–1679. <https://doi.org/10.1016/j.energy.2010.12.063>.
- Guo, Z., Zhao, W., Lu, H., & Wang, J. (2012). Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model. *Renewable Energy*, 37(1), 241–249. <https://doi.org/10.1016/j.renene.2011.06.023>.
- Hinton, G., Deng, L., Yu, D., Dahl, G., Mohamed, A., Jaitly, N., Senior, A., Vanhoucke, V., Nguyen, P., Sainath, T., & Kingsbury, B. (2012). Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal Processing Magazine*, 29(6), 82–97. <https://doi.org/10.1109/MSP.2012.2205597>.
- Homa, M. G., Mengistu Tsidu, G., & Lofton, E. N. (2025). Hydrological modelling and multisite calibration of the Okavango river basin: Addressing catchment heterogeneity and climate variability. *Water*, 17(10), 1442. <https://doi.org/10.3390/w17101442>.

- Huang, L., Zhou, G., Zhang, J., Zeng, Y., & Li, L. (2023). Calculation method of theoretical line loss in low-voltage grids based on improved random forest algorithm. *Energies*, 16(7), 2971. <https://doi.org/10.3390/en16072971>.
- Jamil, M., & Zeeshan, M. (2019). A comparative analysis of ANN and chaotic approach-based wind speed prediction in India. *Neural Computing and Applications*, 31(10), 6807–6819. <https://doi.org/10.1007/s00521-018-3513-2>.
- Jiang, Y., Huang, G., Yang, Q., Yan, Z., & Zhang, C. (2019). A novel probabilistic wind speed prediction approach using real time refined variational model decomposition and conditional kernel density estimation. *Energy Conversion and Management*, 185, 758–773. <https://doi.org/10.1016/j.enconman.2019.02.028>.
- Kulkarni, M. A., Patil, S., Rama, G. V., & Sen, P. N. (2008). Wind speed prediction using statistical regression and neural network. *Journal of Earth System Science*, 117(4), 457–463. <https://doi.org/10.1007/s12040-008-0045-7>.
- Li, F., Ren, G., & Lee, J. (2019). Multi-step wind speed prediction based on turbulence intensity and hybrid deep neural networks. *Energy Conversion and Management*, 186, 306–322. <https://doi.org/10.1016/j.enconman.2019.02.045>.
- Li, Y., Huang, W., Zhao, D., Wang, L., Jiao, Z., Huang, Q., Wang, P., Sun, M., & Yuan, G. (2022). Recent progress in organic solar cells: A review on materials from acceptor to donor. *Molecules*, 27(6), 1800. <https://doi.org/10.3390/molecules27061800>.
- Mi, X., Liu, H., & Li, Y. (2019). Wind speed prediction model using singular spectrum analysis, empirical mode decomposition and convolutional support vector machine. *Energy Conversion and Management*, 180, 196–205. <https://doi.org/10.1016/j.enconman.2018.11.006>.
- Mohandes, M. A., Halawani, T. O., Rehman, S., & Hussain, A. A. (2004). Support vector machines for wind speed prediction. *Renewable Energy*, 29(6), 939–947. <https://doi.org/10.1016/j.renene.2003.11.009>.
- Monfared, M., Rastegar, H., & Kojabadi, H. M. (2009). A new strategy for wind speed forecasting using artificial intelligent methods. *Renewable Energy*, 34(3), 845–848. <https://doi.org/10.1016/j.renene.2008.04.017>.
- Ndhlovu, G. Z., & Woyessa, Y. E. (2021). Use of gridded climate data for hydrological modelling in the Zambezi River Basin, Southern Africa. *Journal of Hydrology*, 602, 126749. <https://doi.org/10.1016/j.jhydrol.2021.126749>.
- NG, A. (2017). *Machine Learning Yearning Book*. <https://info.deeplearning.ai/machine-learning-yearning-book>.
- Pourmousavi Kani, S. A., & Ardehali, M. M. (2011). Very short-term wind speed prediction: A new artificial neural network–Markov chain model. *Energy Conversion and Management*, 52(1), 738–745. <https://doi.org/10.1016/j.enconman.2010.07.053>.
- Ripple, W. J., Wolf, C., Gregg, J. W., Rockström, J., Mann, M. E., Oreskes, N., Lenton, T. M., Rahmstorf, S., Newsome, T. M., Xu, C., Svenning, J.-C., Pereira, C. C., Law, B. E., & Crowther, T. W. (2024). The 2024 state of the climate report: Perilous times on planet Earth. *BioScience*, 74(12), 812–824. <https://doi.org/10.1093/biosci/biae087>.
- Rushdi, M. A., Rushdi, A. A., Dief, T. N., Halawa, A. M., Yoshida, S., & Schmehl, R. (2020). Power prediction of airborne wind energy systems using multivariate machine learning. *Energies*, 13(9), 2367. <https://doi.org/10.3390/en13092367>.

- Šajn, N. (2016). *International Renewable Energy Agency (IRENA)*. Briefing. European Parliamentary Research Service (EPRS). [https://www.europarl.europa.eu/RegData/etudes/BRIE/2016/586662/EPRS_BRI\(2016\)586662_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/BRIE/2016/586662/EPRS_BRI(2016)586662_EN.pdf).
- Salcedo-Sanz, S., Ángel M. Pérez-Bellido, Ortiz-García, E. G., Portilla-Figueras, A., Prieto, L., & Paredes, D. (2009). Hybridizing the fifth generation mesoscale model with artificial neural networks for short-term wind speed prediction. *Renewable Energy*, 34(6), 1451–1457. <https://doi.org/10.1016/j.renene.2008.10.017>.
- Saleh, A. E., Moustafa, M. S., Abo-Al-Ez, K. M., & Abdullah, A. A. (2016). A hybrid neuro-fuzzy power prediction system for wind energy generation. *International Journal of Electrical Power & Energy Systems*, 74, 384–395. <https://doi.org/10.1016/j.ijepes.2015.07.039>.
- Santamaría-Bonfil, G., Reyes-Ballesteros, A., & Gershenson, C. (2016). Wind speed forecasting for wind farms: A method based on support vector regression. *Renewable Energy*, 85, 790–809. <https://doi.org/10.1016/j.renene.2015.07.004>.
- Talla Konchou, F. A., Tiam Kapen, P., Kenfack Magnissob, S. B., Youssoufa, M., & Tchinda, R. (2021). Prediction of wind speed profile using two artificial neural network models: An *ab initio* investigation in the Bapouh's city, Cameroon. *International Journal of Energy Sector Management*, 15(3), 566–577. <https://doi.org/10.1108/IJESM-04-2020-0008>.
- Tulger Kara, G., & Elbir, T. (2024). Evaluation of ERA5 and MERRA-2 Reanalysis Datasets over the Aegean Region, Türkiye. *Dokuz Eylül Üniversitesi Mühendislik Fakültesi Fen Ve Mühendislik Dergisi*, 26(76), 9–21. <https://doi.org/10.21205/deufmd.2024267602>.
- Velo, R., López, P., & Maseda, F. (2014). Wind speed estimation using multilayer perceptron. *Energy Conversion and Management*, 81, 1–9. <https://doi.org/10.1016/j.enconman.2014.02.017>.
- Wang, J., & Li, Y. (2019). An innovative hybrid approach for multi-step ahead wind speed prediction. *Applied Soft Computing*, 78, 296–309. <https://doi.org/10.1016/j.asoc.2019.02.034>.
- Yan, J., Liu, Y., Han, S., & Qiu, M. (2013). Wind power grouping forecasts and its uncertainty analysis using optimized relevance vector machine. *Renewable and Sustainable Energy Reviews*, 27, 613–621. <https://doi.org/10.1016/j.rser.2013.07.026>.
- Xiao, L., Qian, F., & Shao, W. (2017). Multi-step wind speed forecasting based on a hybrid forecasting architecture and an improved bat algorithm. *Energy Conversion and Management*, 143, 410–430. <https://doi.org/10.1016/j.enconman.2017.04.012>.
- Zhang, C., Wei, H., Zhao, X., Liu, T., & Zhang, K. (2016). A Gaussian process regression based hybrid approach for short-term wind speed prediction. *Energy Conversion and Management*, 126, 1084–1092. <https://doi.org/10.1016/j.enconman.2016.08.086>.
- Zhang, Z., Ye, L., Qin, H., Liu, Y., Wang, C., Yu, X., Yin, X., & Li, J. (2019). Wind speed prediction method using shared weight long short-term memory network and gaussian process Regression. *Applied Energy*, 247, 270–284. <https://doi.org/10.1016/j.apenergy.2019.04.047>.
- Zhou, Y., Liu, Y., Huo, Z., & Li, Y. (2022). A preliminary evaluation of FY-4A visible radiance data assimilation by the WRF (ARW v4.1.1)/DART (Manhattan release v9.8.0)-RTTOV (v12.3) system for a tropical storm case. *Geoscientific Model Development*, 15(19), 7397–7420. <https://doi.org/10.5194/gmd-15-7397-2022>.