



Machine Learning Approach to Wind Speed Prediction using Soft Computing Tools

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ABSTRACT

Despite the widespread use of mathematical models in forecasting climatic processes, limited research has been conducted to compare these models. This lack of comparison is particularly significant due to the unpredictable nature of natural wind, which leads to fluctuations in wind power and challenges the stability of wind power systems, hindering the large-scale integration of wind power into the grid. To address this issue, this study proposes a novel wind speed prediction scheme, recognizing the critical role of wind speed prediction in ensuring the safety and stability of wind energy production systems. The research introduces a method that utilizes machine learning models to predict wind speed and optimize the design of energy systems. Two machine learning algorithms are employed in this study: the neural predictor of the Artificial Neural Network, and the classification regression technique, which is especially effective when the number of dimensions exceeds the number of samples, as is often the case with support vector machines (SVM). The dataset used for this research consists of measured and satellite data obtained from the Nigeria Meteorological Agency (NiMet) for the year 2016. The proposed combination forecasting model in this paper demonstrates a well-defined structure and provides reliable predictions. The outcomes presented in this study will advance the field of wind energy prediction, support wind farms in developing wind power control systems, and contribute to the development of sustainable green energy infrastructure.

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INTRODUCTION

Wind energy is widely recognized as one of the most important natural energy sources. Wind is essentially moving air created by changes in atmospheric pressure induced by the sun's uneven heating of the air in the atmosphere and the contour form of the Earth [1][2][3]. It is free, green (clean), and available 24 hours a day, seven days a week for capturing power at a lower cost. The data analysis conducted over the last several years in Nigeria generally indicates that Nigeria offers tremendous prospects for wind energy generation [4]. This is especially true in northern states, mountainous areas of the central and eastern states, and offshore areas where wind is abundant all year [5]. The energy generated by the wind is purely determined by the wind speed in the location, in this case sokoto, where the wind energy conversion system is placed

[6]. A wind turbine is a device that uses wind energy to generate electricity. Wind power, as an alternative to fossil fuels, is readily available, clean, renewable, broadly spread, and emits no greenhouse gas emissions into the environment when in operation [7]. Due to its benefits, there is a general rising interest in the development of wind power in Nigeria. The generation of wind power has expanded dramatically in industrialized nations, notably in Europe, as a result of the need to lessen environmental damage of convectional energy sources [8].

The world cumulative installed capacity of wind power gradually increased from 6100 MW in 1996 to 158,505 MW in 2009 and 743 GW in 2021 [9]. As of 2010, the generation of wind power accounted for over 2.5% of all electrical energy and was expanding at a pace of more than 25% annually. Predicting the electrical energy produced by the wind is

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important in order to use wind power in an electrical system [10]. The predictions of wind power from a few of hours to a few days in advance are significant in the liberalized electricity markets, where the best demanding approach with the least amount of risk is chosen based on anticipated power output and market pricing [11]. There are many of studies and publications on wind speed prediction using Nigeria as a case study, but it's hard to find anything especially on northwest region (Sokoto) that uses Artificial Neural Networks (ANNs) techniques or algorithms for categorizing data to estimate wind speed [12]

MATERIALS AND METHODS

Case Study

The current study was carried out in Sokoto state, which is located in Nigeria's northwestern region. The region is roughly positioned at 11 33° 04 N latitude and 5° 14 E longitude, with a total covering area of 25,973 km² at the extreme part of the Northern region bordering the Saharan Countries. The state has a population of around 3.6 million people (NPC, 2013), including ethnic groupings such as Hausa, Fulani, Zabarmawa, and Tuareg. The Hausa are often regarded as the dominant ethnic group in the region [13] [14][5].

Table 1: Wind speed prediction approach used in this study [15][16]

Forecasting method	Subclass	Examples	Remarks
Statistical method	Time-series models	<ul style="list-style-type: none"> - ARX - ARMA - ARIMA - Grey Predictors - Linear Predictions - Exponential Smoothing, etc. 	<ul style="list-style-type: none"> - Accurate for short-term. - Some very good time-series models supersede ANN structures.
Artificial Neural Network (ANN) method	-	<ul style="list-style-type: none"> - Feed-forward - Recurrent - Multi-layer perception - Support Vector Machine (SVM) - Radial basis function - ADALINE, etc. 	<ul style="list-style-type: none"> - Accurate for short-term. - Their hybrid structures useful for medium to long-term forecasts. - Usually, outperform time-series models.

Methodology

This research was carried out with Sokoto, the state capital, Sokoto as its case study, and the data set was requested and retrieved from Nigerian Meteorological agency (NiNET), National Weather Research Center, located at the Sokoto State University, Sokoto., Nigeria. The data set gotten at NiMET center for Sokoto weather readings 2016 was used in this research work. After preprocessing the data, two models were designed, and two different

techniques were employed using MATABL to forecast wind. These techniques include Artificial Neural network (ANN) and Support Vector Machine (SVM). A Kernel is a function used in SVM for helping to solve problems, proving shortcuts to avoid complex calculations. Through the usage of kernels, we can calculate up to an infinite number of dimensions, enabling the predictions of wind speed from a data sheet of random values given.

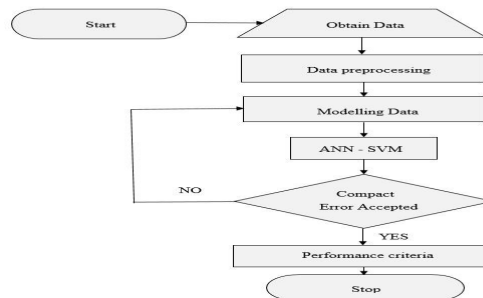


Fig. 1: Proposed Methodology Used in this Study.

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Support Vector Model (SVM)

For classification, regression, and outlier identification, supervised learning techniques called support vector machines (SVMs) are utilized. Support vectors are the vectors that influence the location of the hyperplane and are the closest to it [17][18]. These vectors are termed support vectors because they support the hyperplane. Support vector regression (SVR) is a sort of machine learning regression that uses a learning algorithm capable of classifying and regressing historical data [19][20]. SVR operates according to the statistical learning theory's structural risk minimization (SRM) concept [21]

Artificial Neural Network (ANN)

The goal of artificial neural networks (ANNs), a subset of non-linear statistical models and learning algorithms, is to mimic the actions of connected neurons in biological neural systems [12]. Artificial neural networks also feature neurons that are linked to one another in different levels of the networks, much like the human brain, which has neurons that are coupled to one another [22][23]. Nodes are the name given to these neurons. For a variety of applications, including fault-type classification in TEs, several ANN algorithms have been created [24][25]

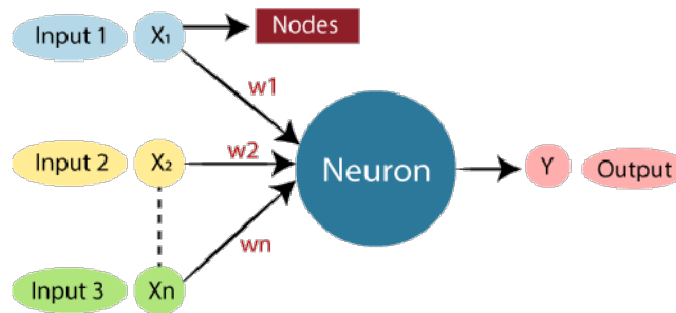


Fig 2: Artificial Neural Network model [22]

The ANN is described by two if-then set of rules for the first order as proposed by Takagi and Sugano.

Rule1: IF x is A_1 AND y is B_1 , THEN.

$$f_1 = p_1x + q_1y + r_1 \quad (1)$$

Rule2: IF x is A_2 AND y is B_2 , THEN.

$$f_2 = p_2x + q_2y + r_2 \quad (2)$$

Performance Criteria

A few performance analysis measures, such as the correlation coefficient (R), coefficient of determination (R^2), mean square error (MSE), and root mean square error (RMSE), were employed to assess the SVM model. The R^2 number, which ranges from 0 to 1, shows the difference between observed and predicted values during training and testing. For the optimal network, the R^2 value should be high, with high values indicating higher agreement and stronger prediction.

$$R^2 = 1 - \frac{\sum_{i=1}^N (OB - PR)^2}{\sum_{i=1}^N (OB - \overline{OB})^2} \quad (3)$$

The Coefficient of Correlation R is important when determining the robustness of the relationship between expected and simulated data points.

$$R = \sqrt{R^2} \quad (4)$$

The root mean square error (RMSE) is a statistical parameter that is often used to compare the forecasting errors of several working models. The lower the RMSE value the better the prediction.

$$MSE = \frac{1}{N} \sum_{i=1}^N (OB - PR)^2 \quad (5)$$

$$RMSE = \sqrt{MSE} \quad (6)$$

These four statistical parameters are essential for evaluating the efficiency of each

predictive method in this analysis of selecting the best predictive model at high accuracy. Where OB is the observed data, PR is the predicted data, OB is the average of the observed data and N is the number of data obtained [26].

Data Used and Model Validation.

In the statistical analysis aspect, the validation amount was 70-30, 70% for training, 30% for testing, where the data attained from the data set is the Observed data, while the predicted data is the data gotten from MATLAB created. In this study, we used four working models for our prediction in MATLAB namely.

- M1 F(Rh),
- M2 F(Rh+MaxT),
- M3 F(Rh+MaxT+Sr),
- M4 F(Rh+MaxT+Sr+P+MinT).

RESULTS AND DISCUSSION

For a distant area in Sokoto, Nigeria, long-term load forecasting has been accomplished. The SVM model was used to predict wind speed. The Spearman-Pearson correlation, which shows the relationship between the variables (solar radiation, maximum temperature, relative humidity, lowest temperature, precipitation, and wind speed), is used in this study to determine the model input combinations. The strength of the correlation in this case is unaffected by the inverse or direct link between the variables. From the figure below, the variable contribution to wind speed is 26%, 15%, -2%, -36% and 20% by maximum temperature, minimum temperature, precipitation, relative humidity, and solar radiation respectively.

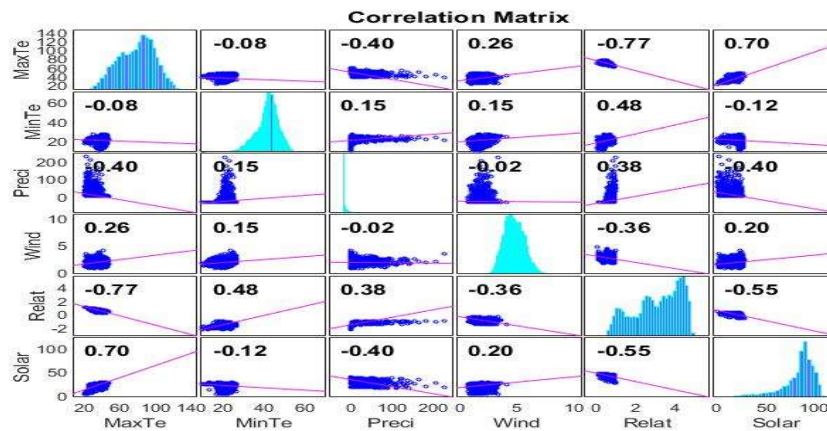


Fig 3: Correlation matrix of dataset

To prevent over fitting caused by various causes, adequate number of hidden nodes was determined in the ANN modelling. The linear SVM algorithm, under regression

learner is used in training the model, due to its excellent performance in recent studies. Here below show the Performance criteria of the model.

Table 2: Statistical data from performance criteria of the model

	Calibration (Training)					
	MSE	RMSE	MAE	MAPE	R ²	R
SVM 1	0.152772	0.39086	0.308603	17.62%	0.109072	0.330261
SVM 2	0.213405	0.461958	0.379301	24.43%	-0.24453	0.494497
SVM 3	0.21465	0.463303	0.380058	24.31%	-0.25179	0.501785
SVM4	0.227365	0.476828	0.390052	24.89%	-0.32594	0.570909
	Verification (Testing)					
	MSE	RMSE	MAE	MAPE	R ²	R
SVM 1	0.14158	0.376272	0.295991	18.45%	0.146583	0.382861

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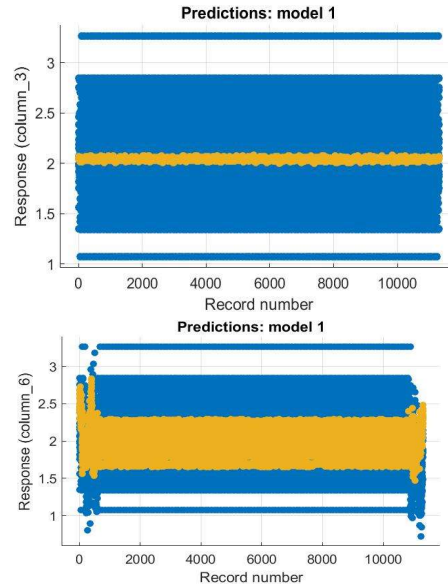
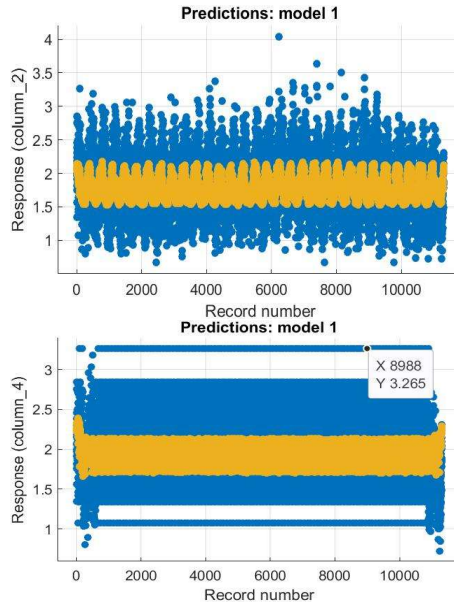
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Calibration (Training)						
	MSE	RMSE	MAE	MAPE	R ²	R
SVM 2	0.241176	0.491097	0.405652	27.67%	-0.45376	0.673618
SVM 3	0.245839	0.495822	0.408739	27.71%	-0.48187	0.694168
SVM4	0.250883	0.500882	0.41133	27.83%	-0.51227	0.715733

The first combination, SVM 1, has a high accuracy based on its positive value to the coefficient of determination, the others are a

poor fit for the data, meaning that they are not explained by the model.



CONCLUSION

This paper demonstrates a method for using machine learning models to estimate wind speed and optimize wind energy production. Machine learning nonlinear based models are accurate in predicting the variation with low error, according to the study. To predict wind speed variation, both ANN, a well-known AI-based model, and SVM, a linear model, are used. Raw data are fed into mathematical models in relation to the designated locations in Sokoto using the neural predictor ANN-SVM. Thereafter, a comparative analysis was carried out to see how accurate these models were at predicting the future. The findings showed that, in order to satisfy consumer expectations, the relative humidity of the environment is the most reliable element for estimating strong wind speed. Furthermore, investigations demonstrated that Support Vector Model is

accurate for predicting the wind speed with low error.

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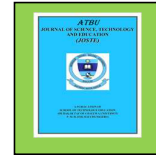
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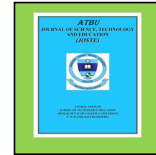
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