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Wind Speed Prediction Using Artificial Intelligence: A Case Study, Abuja, Nigeria

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ABSTRACT: The accurate prediction of Wind Energy Speed (WES) is very important and essential for monitoring, controlling, planning and distribution of generated power to meet consumers need due to the shortage in electricity supply in Abuja. This study investigates the Artificial Neural Network (ANNs) method for the implementation of Support Vector Machine (SVM) algorithm, for classification, regression, and outlier detection for the forecasting of wind speed from local meteorological training data gotten from the Nigerian Meteorological agency (NiMET), National Weather Research Center, located at Nnamdi Azikiwe International Airport, Bill Clinton Dr, 900102, Abuja, Nigeria from a period of over thirty years (1983-2013). The dataset is carefully pre-processed to handle missing values and outliers. The experimental results demonstrate that the SVM model outperforms alternative methods in terms of wind speed prediction accuracy. The findings of this research highlight the efficacy of SVM in wind speed prediction, showcasing its potential for practical implementation in wind energy systems.

KEYWORDS: Wind Energy Speed (WES), Support Vector Machine (SVM), Energy, Forecasting, Artificial Neural Network (ANN).

I. INTRODUCTION

Wind energy is widely known to be one of greatest sources of natural energy. Wind is basically air in motion which is caused by differences in atmospheric pressure because of the sun's uneven heating of the air in the atmosphere and contour shape of Earth. Unlike conventional power plants, wind power, which is alternative to fossil fuels, is readily available, clean, renewable, widely distributed, and produces no greenhouse gas emissions to the environment during operation [2]. Due to its benefits, there is a general growing interest in the development of wind power in Nigeria. The generation of wind power has expanded dramatically in industrialized nations, especially in Europe, as a result of the need to lessen environmental damage of convectional energy sources. Wind energy's total installed capacity worldwide rose through time, going from 6100 MW in 1996 to 158,505 MW in 2009 and 743 GW in 2021 [3][4]. Tunisia, Morocco, and Egypt were the top three wind-power producing nations in Africa 11 years ago, with installed capacities of 54 MW, 253 MW, and 430 MW, respectively [3]. Around 83 nations used wind power for commercial purposes in the world in 2011. As of 2010, the production of wind power accounted for about 2.5% of all electricity generated globally and was expanding at a rate of more than 25% annually. Predicting the electrical energy produced by the wind is important to use wind power in an electrical system [5].

Several works on prediction and forecasting of renewable energy sources using machine learning has been conducted in recent times [17][24][25][28]. The data analysis conducted over the past few years in Nigeria usually shows that there are numerous prospects for wind energy production in Nigeria [1]. This is especially true in northern states, mountainous regions of central and eastern states, and offshore regions, where wind is plentiful all year long. In the instance of the study, Abuja, where the wind energy conversion system is proposed, the amount of energy generated by the wind will simply depend on the local wind speed.

A. Case Study – Federal Capital Territory, Abuja

Nigeria's capital, Abuja, is situated in the Federal Capital Territory (FCT), the middle of the nation. Under the direction of the former President of Nigeria, General Ibrahim Badamasi Babangida, it was formed on the 3rd of February 1976 from pieces of Niger state, Nasarawa state, and Kogi state. On the 12th of December 1991, it was formally designated as the nation's capital (1985-1993) [6]. As depicted in figure 1, Abuja is located in the North-Central region of Nigeria and is home to six area councils: Abaji, Gwagwalada, Kwali, Kuje, Bwari, and Municipal Area Council [8]. 3,464,123 people are anticipated to live in Abuja in 2021. The population was 18,977 in 1950. Since 2015, Abuja has increased by 186,383, or 5.69 percent annually [9]. These population projections and estimates are based on the most recent update to the UN's World Urbanization Prospects [10]. The Federal Capital Territory, Abuja, is located at 9.072264, 7.491302 [12][17][26] and is surrounded by nature in accordance with the master plan created on the grass covered Chukuku Hills during the 1980s. Its municipal area is 1,769 km2 (683 sq. mi), while its urban area is 713 km2 (275 sq. mi) [7].

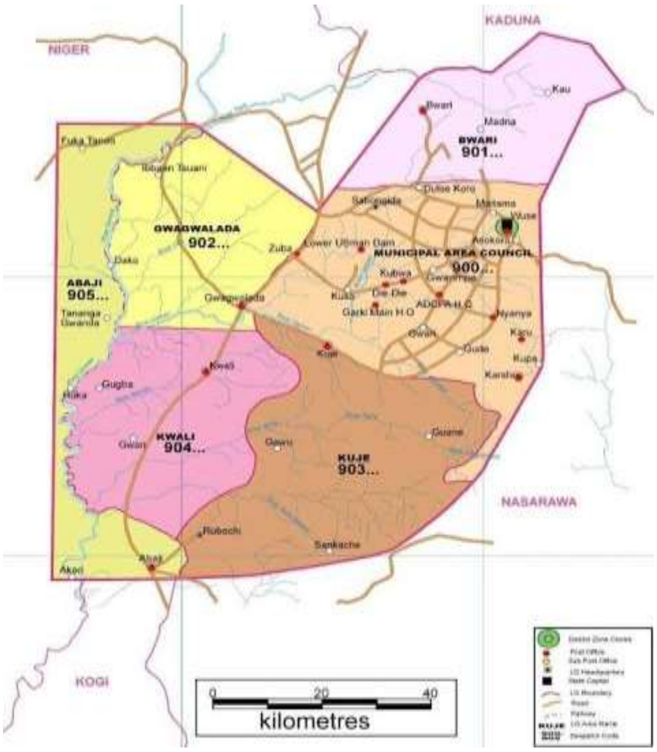


Figure 1. Map of Abuja Showing the Six Area Councils [11].

Large-scale wind flow is mostly caused by the planet's rotation and the difference in temperatures between the equator and the poles (Coriolis effect). According to their spatial scale, speed, direction, force behind them, location of occurrence, and impact, wind is categorized (strength). Gusts are defined as brief periods of extremely fast wind. Squalls are strong winds with a minute or less in duration. Long-lasting winds are referred to by a variety of titles depending on their average strength, including Breeze, Gale, Storm, and Hurricane [13].

Abuja is 360 meters (1,180 feet) above sea level. The tropical wet and dry climate (Koppen: Aw) that falls under this classification has three different weather conditions each year. This contains a scorching dry season and a warm, muggy wet season. The northeast trade wind causes a brief harmattan interlude between the two, with the main characteristics being dryness and dust haze [14].

The ability to predict wind speed is crucial because it influences many different aspects of daily life, including the amount of electricity produced, weather forecasting, aviation and maritime operations, construction projects, plant growth and metabolism, farm chores like irrigation and wine pressing, and the timing of daily activities like hang gliding and kite flying, among many others. [15][16]. Predicting the wind speed would help to solve this issue because the fundamental barrier to wind power's inclusion into the electrical system is its erratic nature.

Over the past few years, several wind speed forecasting techniques have been documented in various literatures; each methodology or method has a specific time scale to which it can be applied for the most accurate results. The table I below shows how various prediction techniques are classified according to their time scales:

Table I. Time-scale Classification for Different Forecasting Techniques [18][19][20][21].

Time horizon	Range	Applications
Very short term	Few minutes to one hour ahead	•Electricity market clearing •Real-time grid operations • Regulation actions
Short term	One hour to several hours ahead	• Economic load dispatch planning •Load reasonable decisions • Operational security in electricity market
Medium term	Several hours to one week ahead	•Unit commitment decisions • Reserve requirement decisions •Generator online/offline decisions
Long term	One week to one or several year(s) ahead	• Maintenance planning and operation management • Optimal operating cost • Feasibility study for design of the wind farm

The proposed method or technique for forecasting wind speed from data gotten at NASRDA station in this study is the Support Vector Method (SVM), an ANN approach.

B. Artificial Neural Network (ANN)

The biological neural networks that shape the structure of the human brain are where the phrase "artificial neural network" originates. Artificial neural networks also feature neurons that are interconnected to one another in different levels of the networks, much like the human brain, which has neurons that are coupled to one another. Nodes are the name given to these neurons [22].

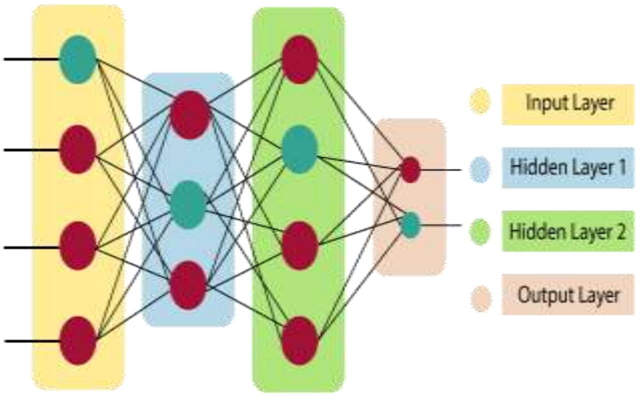


Figure 2. Architecture of an Artificial Neural Network [25]

Input layer: The values of the explanatory attributes for each observation are to be provided as input to the input layer. The number of explanatory variables is equal to the number of input nodes in an input layer. The network receives the patterns from the "input layer," which then sends them to one or more hidden layers [23].

Hidden layer: The input values inside the network are subjected to the modifications applied by the hidden layers. A set of weighted connections is used in the hidden layer to carry out the actual processing. One or more hidden layers might exist. Weights are a collection of predetermined numbers contained in the program that are multiplied by the values entering a hidden node. A single number is then generated by adding the weighted inputs [23].

Output layer: Connections are sent from input layer or hidden layers to the output layer. It provides an output value that is consistent with the response variable's forecast. Most categorization issues have a single output node. To create the output values, the active nodes of the output layer aggregate and modify the data [23].

C. Support Vector Model (SVM)

Support vector machines (SVMs) are a group of supervised learning techniques for classifying data, performing regression analysis, and identifying outliers. The vectors that are closest to the hyperplane and have an impact on the hyperplane's position are called support vectors. These vectors are referred to as support vectors because they aid the hyperplane.

Support vector regression (SVR) is a kind of machine learning regression that uses a learning algorithm that can analyze historical data for regression and classification. The statistical learning theory's structural risk minimization (SRM) principle underlies SVR's operation [53], [54].

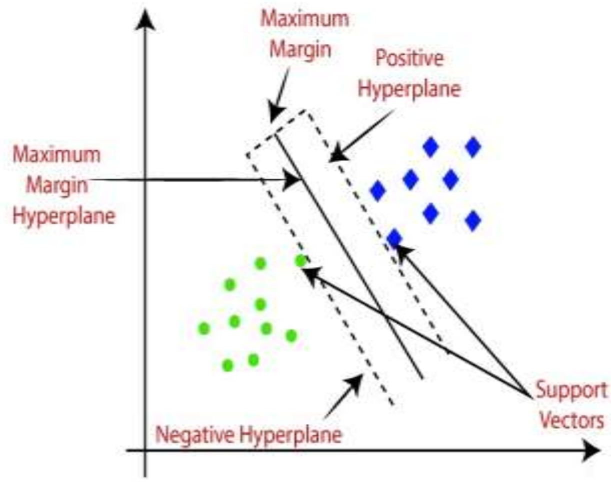


Figure 3. SVM Graphical Representation Showing How Two Different Categories are Separated by Hyperplane [55].

II. METHODOLOGY

The Abuja Meteorological data set was collected from the Nigerian Meteorological agency (NiMET), Abuja then identified and retrieved at Baze University, Airport Road from the Department of Electrical and Computer Engineering. In this study, four working models for the prediction in MATLAB are used, namely,

1. Ws=M1 F(Rh),
2. Ws=M2 F(Rh+MaxT),
3. Ws=M3 F(Rh+MaxT+Sr),
4. Ws=M4 F(Rh+MaxT+Sr+P+MinT).

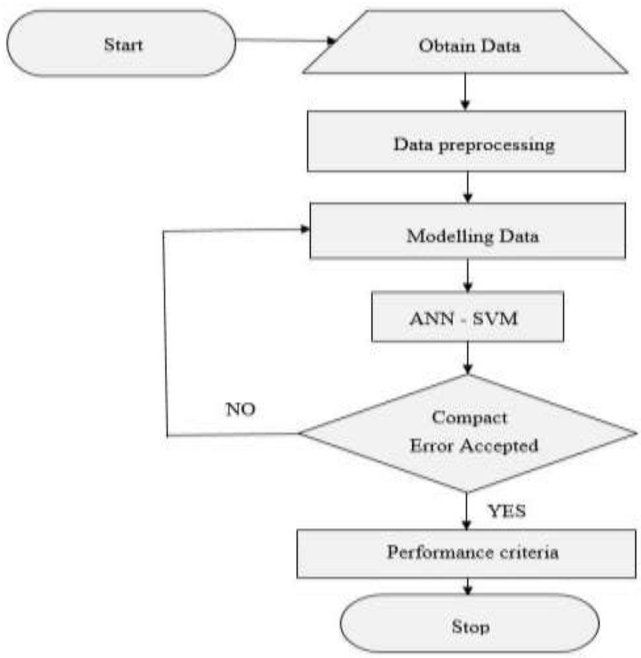


Figure 4. Flowchart of Methodology

A. Evaluation criteria of model

The SVM model was assessed using several performance analysis measures, such as the correlation coefficient (R), coefficient of determination (R^2), mean square error (MSE), and root mean square error (RMSE). The R^2 number, which ranges from 0 to 1, shows the difference between observed and predicted values during training and testing. For the best network, the R^2 value should be high, with high values indicating higher agreement and stronger prediction. [17][27]

Coefficient of Determination, $R^2 = 1 - \frac{\sum_{i=1}^{N}(OB-PR)^2}{\sum_{i=1}^{N}(OB-\overline{OB})^2}$ (1)

Coefficient of Correlation, $R = \frac{\sum_{i=1}^{n}(OB-\overline{OB})(PR-\overline{PR})}{\sqrt{\sum_{i=1}^{n}(OB-\overline{OB})^2(PR-\overline{PR})^2}}$ (2)

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

Mean Squared Error, MSE = $\frac{1}{N}\sum_{i=1}^{N}(OB-PR)^2$ (3)

RMSE= $\sqrt{(\frac{1}{N}\sum_{I=1}^{N}(OB-PR)^2)}$ (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.

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, $\overline{OB}$ is the average of the observed data and N is the number of data obtained.

III. RESULT AND DISCUSSION

For a remote area in Abuja, Nigeria, long-term load forecasting has been accomplished. The SVM model was used to anticipate wind speed. The Spearman-Pearson correlation, which illustrates the relationship between variables, is used in this study to derive the model input combinations (solar radiation, maximum temperature, relative humidity, minimum temperature, precipitation, and wind speed).

The strength of the correlation in this case is unaffected by the inverse or direct link between the variables. As seen in figure 5 below, the maximum temperature, minimum temperature, precipitation, relative humidity, and solar radiation are the variables that have the greatest impact on wind speed, contributing 26 percent, 15 percent, 2 percent, -36 percent, and 20 percent, respectively.

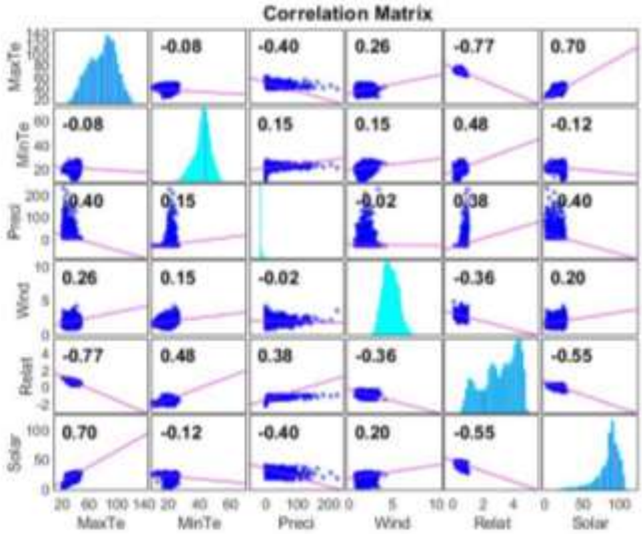


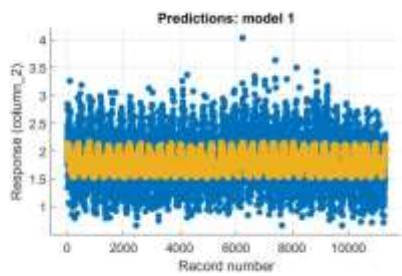
Figure 5. Correlation Matrix of Dataset

The SVM model is implemented using MATLAB software (R2019b) and Microsoft Excel (2016). A sufficient number of hidden nodes was established in the ANN modelling in order to prevent overfitting brought on by numerous factors. Due to the linear SVM algorithm's outstanding performance in recent studies, regression learner is employed to train the model. The model's performance criteria is shown in Table II below.

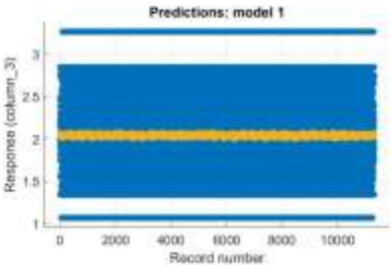
Table II. Performance Criteria of the Model

	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
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

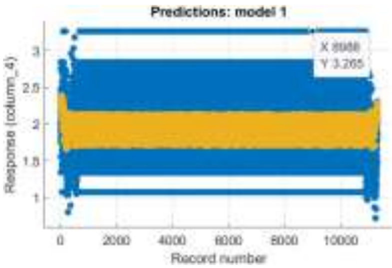
Based on its positive coefficient of determination value, the first combination, SVM 1, has a high accuracy whereas the rest are a poor fit for the data.



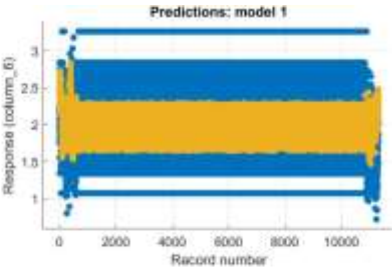
(a) ANN-SVM 1



(b) ANN-SVM 2



(c) ANN-SVM 3



(d) ANN-SVM 4

Figure 6 (a – d). ANN-SVM model combination prediction visualization for M1, M2, M3, M4

CONCLUSIONS

Strong machine learning algorithms like SVM are known for their prowess in handling high-dimensional data and nonlinear relationships. This study suggests a method for using machine learning models to forecast wind speed and optimize wind energy harvesting. The neural predictor ANN-SVM is used to feed raw data for solar radiation, temperature, relative humidity, wind speed and precipitation into mathematical models relative to the specified regions in Abuja. The results revealed that the relative humidity in the environment is the most effective factor for determining strong wind speed in as much as to meet consumer needs.

The comparison between the projected and actual data from the meteorological stations showed excellent agreement. The conventional predictions that are now available are quite dynamic because any forecast is only really accurate 24-48 hours in advance and even then, can change many times.

Investigations further revealed that the Support Vector Model has a low inaccuracy in predicting wind speed. The suggested method can considerably improve grid integration, planning, and administration of renewable energy sources, as well as the operation and maintenance of wind farms. To further improve the accuracy and resilience of wind speed forecasting models, future research can investigate ensemble methodologies and incorporate other meteorological factors.

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