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Solar Radiation Forecasting Using Adaptive Neuro Fuzzy Inference System (ANFIS)

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ABSTRACT: Hybrid intelligent systems have previously been centered on forecasting solar energy using meteorological data parameters; nevertheless, such forecasting approaches have yielded unreliable results. The goal of this research is to design and develop ANFIS model for forecasting solar energy based on widely shifting environmental factors utilizing experimental data collected in Abuja. This is accomplished by developing a system that predicts solar energy generation using an Artificial Neural Network (ANN) and fuzzy logic. This research examines four Adaptive Neuro Fuzzy Inference System (ANFIS) models that were developed and tested in Abuja, Nigeria, for horizontal sun radiation prediction. These models were generated by varying the number of inputs for each model with the output being solar radiation. Data set of 30 years were collected from the National Space Research Development Agency (NASDRA) and procured for the presented simulation study. Simulation using ANFIS methodology was carried out using MATLAB Tool. The obtained data was divided into two categories: training and testing with training having 70% and testing 30% of the data sets. The simulation results were checked against the data and confirmed to be within allowable limits. The coefficients of determination (R^2), correlation coefficient(R), Mean Square Error (MSE), Root Mean Square Error (RMSE) were calculated to demonstrate the effectiveness of the proposed machine learning models. It can be safely concluded that model 4 gave an accurate result with high efficiency and less error.

KEYWORDS: Solar Energy, Adaptive Neuro Fuzzy Inference System (ANFIS). Solar Forecasting, Artificial Neural Network (ANN)

I. INTRODUCTION

Solar energy has the ability to lead the nation toward long-term and sustainable progress as it is a plentiful and practical energy source. The majority of Nigeria's power is produced using fossil fuels including gas, oil, and coal, and only 40% of the country's population has access to the national grid [1]. The goal of solar power forecasting is to lessen the impact of solar intermittency by gathering and analyzing data to estimate solar power generation over a range of time periods. For effective grid management and power trading [2], solar radiation predictions are used, allowing grid operators to predict and balance energy supply and demand more effectively. However, artificial intelligence (AI) has recently been acknowledged and applied for solar radiation prediction with higher accuracy [4]. Many researchers have employed empirical methodologies for forecasting solar radiation [3].

A. Related Works

[5] Developed a hybrid solar radiation prediction model using ARMA and Time Division Neural Network (TDNN). The outcomes show that the two techniques combined outperform ARMA and TDNN separately. In a recent study, [6] proposed a deep learning method for computing daily global sun radiation based on embedding clustering (EC) and functional Deep Belief Networks (DBN). The technique improved the accuracy of the estimation according to the average values at the 30 stations, achieving 1.706 MJ/m2 of mean absolute error (MAE), 2.352 MJ/m2 of root mean square error (RMSE), and 13.71 percent of mean absolute percentage error (MAPE). [7] Compares the long short-term memory (LSTM), a novel forecasting technique from the deep neural network family, to competing techniques that have a proven track record in forecasting solar energy. Empirical results show that LSTM outperforms a wide range of rival techniques by a substantial margin, with an average forecast skill of 52.2 percent over the persistence model.

Many studies, including [8][9][10][11][24][25][26], have used machine learning techniques to conduct research. ANN models have been used in a range of applications, such as least-square optimization for numerical weather prediction and optimal estimation and forecasting. In Jamshid's study [12], empirical models and nonlinear models, including the adaptive neuro-fuzzy inference system (ANFIS) and the neural network auto-regressive model with exogenous inputs (NN-ARX), were used to predict solar radiation. The outcomes were compared. The findings showed that ANFIS and NN-ARX performed better at estimating daily solar radiation than empirical models.

Based on historical data for Abuja, this work seeks to optimally design a comprehensive model to forecast solar radiation.

B. Solar Energy Demand in Nigeria

Nigeria receives an average of 6 hours of sunlight and 19.8 MJm2/day of solar energy. According to the Nigerian government's Renewable Energy Master Plan, which targets for 500 MW of solar PV installed capacity by 2025, renewable energy would make up 30% of all energy generation by 2030. [13] Around 427,000 megawatts (MW) of potential concentrated solar power and photovoltaic output have been estimated [14]. In coastal latitudes, the annual average of total solar radiation ranges from about 12.6-28MJ/m2 per day to about 25.2MJ/m2 per day. Inferring that Nigeria's entire geographical area receives an average of 6,372,613 PJ/year, or about 1,770,00TWh/year, of solar energy over the course of a year yields an annual average solar intensity of 1935.5KWh/m2.

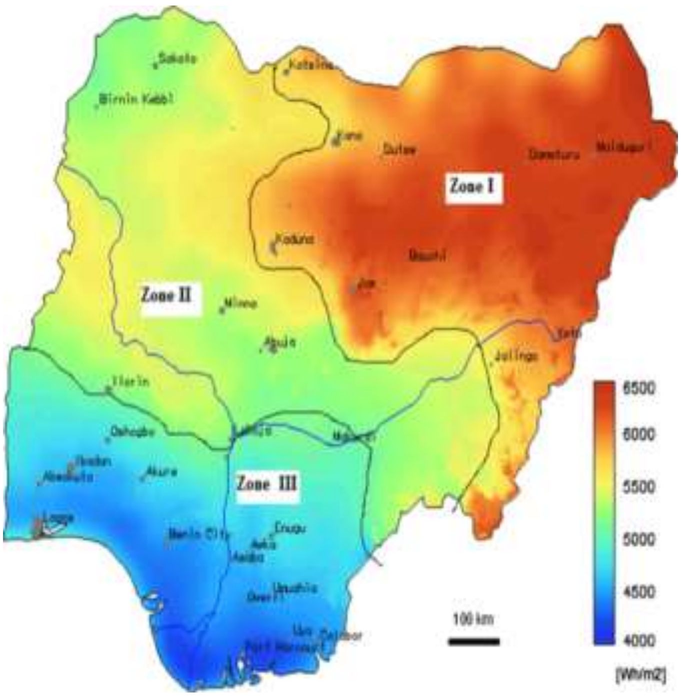

Figure 1: Map of Nigeria Showing Solar Irradiation [15]

The distribution of solar radiation across Nigeria is depicted on a map in Figure 1. The highest potential for solar radiation is found in Zone I states, which are followed by Zone II and Zone III states, respectively [14]. The study was conducted in Abuja, a city in northern Nigeria that spans an area of about 8000 km2 and is situated north of the meeting point of the Niger and Benue rivers. Abuja is situated 840 meters (2760 feet) above sea level at latitude 9.07N and longitude 7.48E. [16] [14]

II. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

The artificial neural network ANFIS is created using the Takagi Sugeno Fuzzy Inference System (Jang, 1993). The strategy was developed in the start of the 1990s. The Takagi sugeno model of the ANFIS is an adaptive network type that is functionally equivalent to fuzzy inference systems. ANNs and fuzzy logic are used in the Artificial Neural Network (ANN), a soft computing paradigm. The qualitative aspects of human comprehension are changed by fuzzy thinking, and it also offers fresh perspectives on the precise quantitative analysis process. However, it lacks a standardized mechanism for transforming human thought into a rule-based fuzzy inference system (FIS) and modifying the membership functions (MFs) takes a lengthy time. It has a stronger ability to adjust to its surroundings throughout the learning process than ANN [18]. As a result, ANN can be used to automatically alter the MFs and lower the rate of errors in the determination of fuzzy logic rules. It's used in a situationally aware intelligent energy management system [19]. The chain law, as well as gradient descent or back propagation, are typically employed to learn the basic adaptive network.

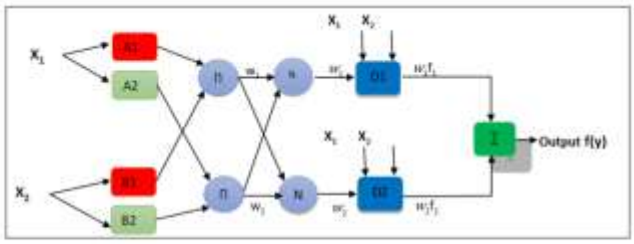

Figure 2: ANFIS structure [20]

Figure 2 depicts the ANFIS architecture with two inputs, x and y. The functions of nodes in the same layer are comparable. The output of the ith node in layer l is labeled,o-i. The neuro fuzzy network is a five-layer feed forward network that uses a neural network learning algorithm with fuzzy reasoning to translate an input space to an output space. The input series are converted to fuzzy inputs in the ANFIS model by employing a membership function for each input series. The shape of the membership function is determined by the data set [21].

III. PROPOSED METHODOLOGY

The National Space Research Development Agency (NASDRA) Data was used to retrieve yearly measured climatic parameters such as maximum and minimum temperatures, relative humidity, precipitation, wind, and solar radiation on the horizontal surface for a period of 30 years, ranging January 1983 to December 2013. For circumstances where a variable was missing, data pre-processing was performed on the data. For each parameter where missing variables were observed, the difference between the highest and minimum value was divided by two.

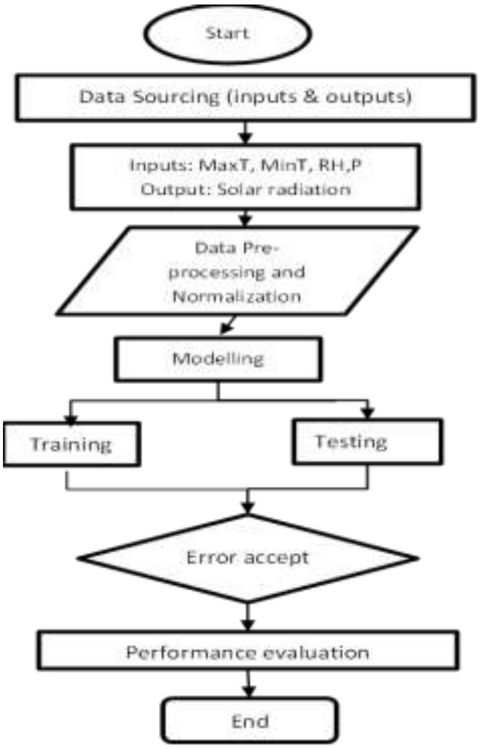

Figure 3: Flowchart of proposed Methodology

By combining the inputs and outputs into four (4) different ANFIS models, four (4) different ANFIS models were created. The input data for the first model included maximum temperature and output solar radiation values. The second model included maximum temperature and relative humidity, with solar radiation as the output. The third model comprised three inputs: maximum temperature, relative humidity, and wind speed, with solar radiation as the output value. Maximum temperature, relative humidity, wind speed, precipitation, and minimum temperature are among the five-input data for the fourth model. The correlations provided by the ANFIS correlation plot from the MATLAB routines were used to identify model combinations.

Table 1: Model Combination of System

MODEL	INPUTS	OUTPUT
M1	MaxT.	Solar radiation
M2	MaxT, RH.	Solar radiation
M3	MaxT, RH, Wind speed.	Solar radiation
M4	MaxT, RH, Wind speed, P, MinT.	Solar radiation

Coefficients of Determination (R^2), Correlation Coefficient (R), Mean Square Error (MSE), and Root Mean Square Error (RMSE) are among the performance evaluation criteria used to evaluate the models [22][23][24]. The parameters are:

$$R^2 = 1 - \frac{\sum_{J=1}^{N}|X_i - Y_i|^2}{\sum_{J=1}^{N}|X_i - X_m|^2} \quad (1)$$

$$R = \frac{\sum_{i=1}^{n}(X_i - X_m)(Y_i - Y_m)}{\sqrt{\sum_{i=1}^{n}(X_i - X_m)^2 (Y_i - Y_m)^2}} \quad (2)$$

$$\text{RMSE}=\sqrt{\left(\frac{1}{N}\sum_{I=1}^{N}(x_i - y_i)^2\right)} \quad (3)$$

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \quad (4)$$

Where n, X_i, X_m, Y_i Y_m are data number, observed data, average value of the observed data and predicted values respectively

IV. RESULT AND DISCUSSION

A comparison of four non-linear artificial intelligence models (ANFIS) for estimating solar radiation is proposed in this research. The grid partitioning strategy enhanced the forecast accuracy. In both the training and testing phases, the modeling outcomes were evaluated using R, R2, MSE, and RMSE. Using classic sensitivity analysis and a correlation matrix, the most dominant and suitable input combinations with the relevant variables were evaluated. The matrix in Table 1 represents the sort of linear relationship between the variables. It can also be used as a rudimentary indicator of variable set correlation. The stationary and significant variables with probability less than 0.05 (P0.05) imply a strong strength of linear correlations, as illustrated in Fig 4. In addition, the negative correlation values indicate that the two variables have an inverse association. As a result, the correlation value's weakness suggests that standard methods are inefficient in simulating such complicated connections, and that new robust tools are urgently needed.

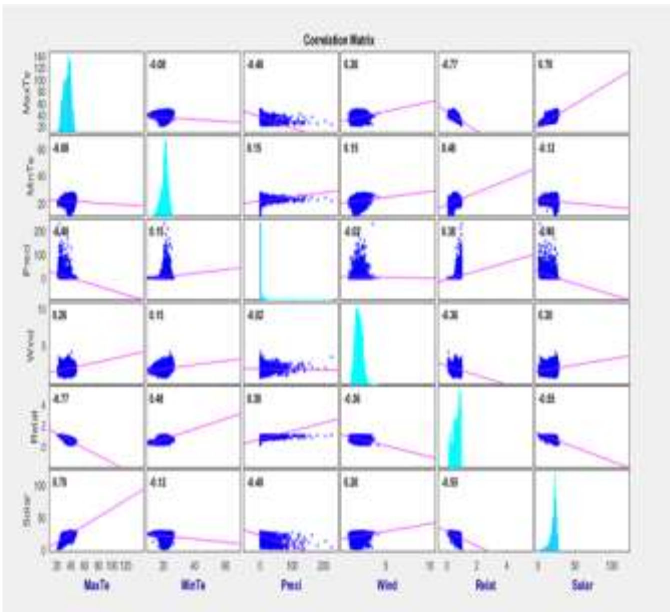

Figure 4: Correlation Matrix of Experimental Variables

The model combinations were created based on the level of interaction between each variable and solar radiation as shown in Figure 4. With a value of 0.70, MaxT has the best relationship, while MinT has the worst relationship with a value of -0.12. M1, M2, M3, and M4 are the created models for usage in ANFIS. The normalized atmospheric variables and Rs were utilized as variables in the modeling. The Neuro-Fuzzy Designer program in MATLAB was used to forecast sun radiation with ANFIS. A Sugeno type fuzzy inference system was created by tuning the input and output parameters of the membership function (MF). A triangular MF type was chosen for the input parameter, and a constant MF type was chosen for the output parameter. For 50 iterations, the FIS was trained using a 0.005 error tolerance (epochs).

To adequately evaluate the effectiveness of ANFIS in forecasting solar radiation, the forecasted solar radiation values produced by the ANFIS model were partitioned into training (70%) and testing (30%). Table 2 displays the outcomes of the performance criterion. M4 gave the best training outcomes among the models, with values of R^2 = 0.700737, R =0.8371, MSE =7.08919, and RMSE =2.662553.

Table 2: Training Phase (70%)

	R^2	R	MSE	RMSE
M1	0.590231	0.768265	9.706938	3.115596
M2	0.645167	0.803223	8.405584	2.899239
M3	0.652977	0.80807	8.220569	2.867153
M4	0.700737	0.8371	7.08919	2.662553

Table 3: Testing Phase (30%)

	R^2	R	MSE	RMSE
M1	0.5734	0.757232	9.333315	3.055048
M2	0.62692	0.791783	8.16237	2.856986
M3	0.638554	0.799096	7.907849	2.81209
M4	0.670259	0.818693	7.214192	2.685925

The finding is supported by radar plots of R^2, R, and MSE values in both the training and testing models for ANFIS (M1-M4). Rader plots, also known as spider plots, have a scale of 0 to 1 and are useful for determining which variables in a dataset have low or high scores, making them great for reporting performance.

(a) (b)

Figure 5: ANFIS Radar Plots of R^2 and R for Training and Testing

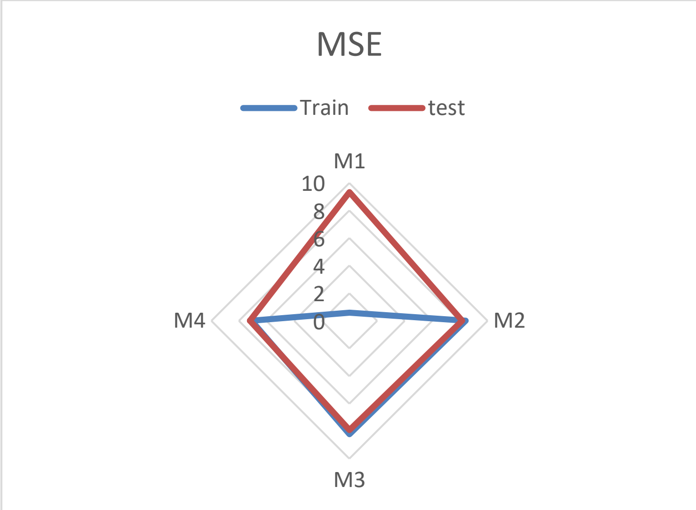

Figure 6: ANFIS Radar Plots of MSE for Training and Testing.

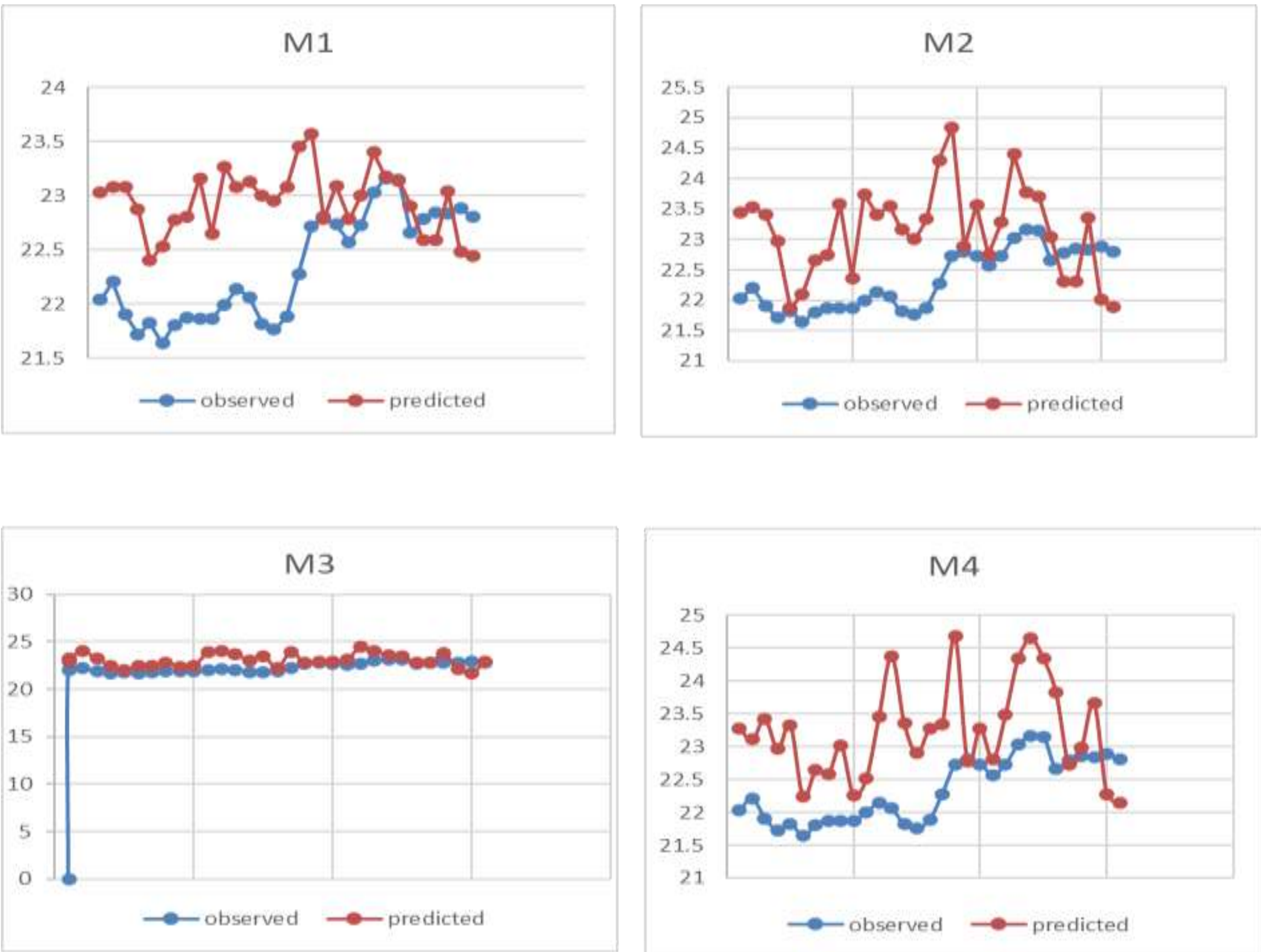

Figure 7: Time Series Plot for ANFIS models M1, M2, M3, and M4

The models were examined using a time series plot (figure. 7) to show how the observed and anticipated solar radiation values change over time, indicating the degree of agreement between the variables. When such variables in the plot overlap, that is, when their patterns of time variation are comparable, such variables agree. Figure 7 provides a time series plot for the best ANFIS model (M4), which indicates that the predicted and observed values are virtually identical. This indicates that the observed and projected values are in a high degree of agreement.

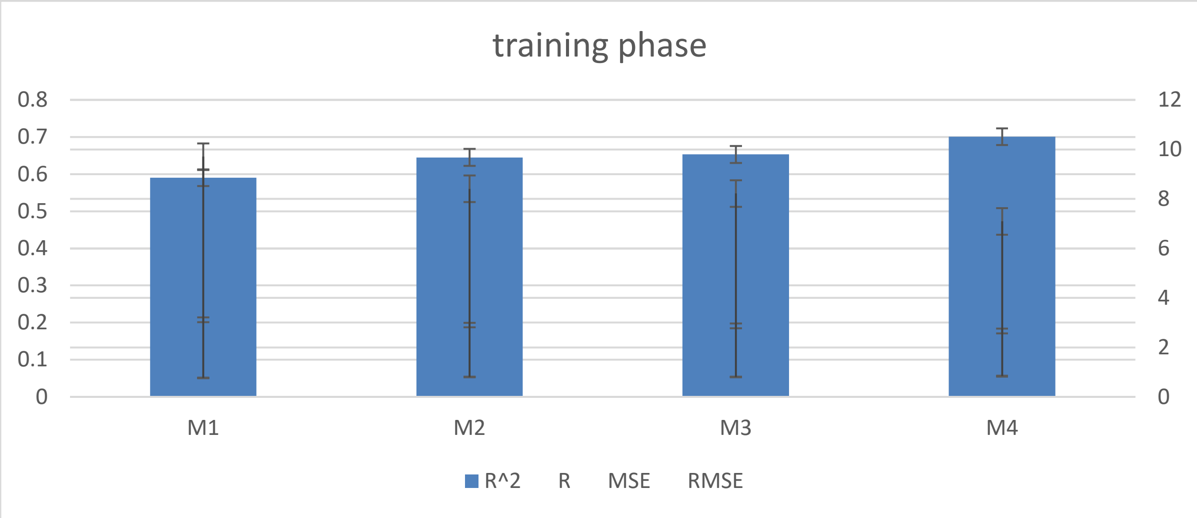

Figure 8: Box Plot Showing the Training phase of the Observed and Predicted Solar Radiation

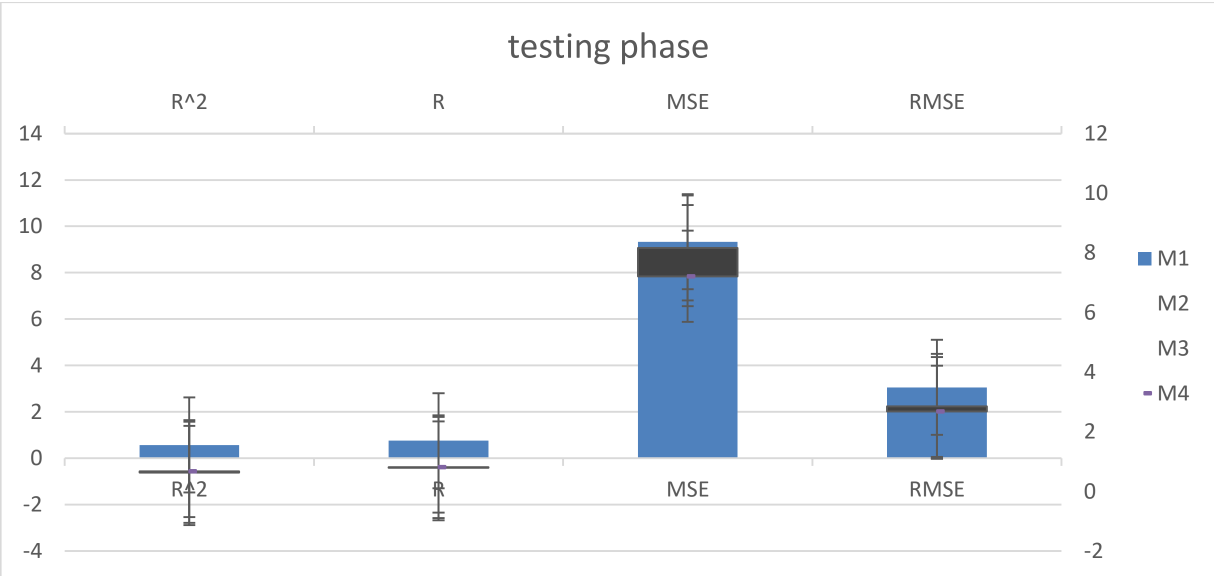

Figure 9: Box Plot Showing the Testing Phase of the Observed and Predicted Solar Radiation

CONCLUSIONS

The performance of four different model combinations of a hybrid machine learning model (ANFIS) in Abuja, Nigeria, was investigated and compared to see which was the most suitable and accurate for solar forecasting. The study's goal is to offer meaningful solar radiation data for monitoring solar radiation variation in Abuja, which is important not only for solar power plant construction, but also for long-term administration and operation of solar systems. The goal of this research is to employ generally available measured environmental data as inputs to boost solar radiation (maximum and minimum temperatures, relative humidity, precipitation, and wind speed) (the output). The input parameters were chosen because they are widely available for all locations, have a strong correlation with the output (solar radiation), and are simple to get. The following are the findings of the study, which are based on long-term data collection:

i. When dealing with more input parameters, the ANFIS model looks to be both computationally efficient and adaptive. As a result, the model can be used as a module to predict solar radiation data based on other commonly known meteorological characteristics.

ii. M4 delivered outcomes that were more efficient and had less errors, according to the statistical performance of the metrics acquired. M4 had a dependability of 0.700737 and a root mean square error of 2.662553.

iii. M4 surpasses the other models in terms of coefficient of determination when estimating solar radiation.

iv. Maximum temperature and relative humidity are crucial characteristics required to effectively predict solar radiation, according to the correlation diagram.

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