Improving the Prediction of Solar Radiation Using ANFIS Optimization Ensemble

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ABSTRACT

A reliable design and monitoring of solar energy-based systems, requires accurate information on the available solar radiation. However, measurement of solar radiation is difficult due to the high cost of measuring devices, together with their calibration and maintenance, particularly in developing countries like Nigeria. Meanwhile, solar radiations in such regions are often predicted using data-driven techniques. Nevertheless, the existing predictive models often produce unsatisfactory results. This study proposed the development of intelligent models for forecasting of solar radiation in Kano state, Nigeria. The model is developed using ensemble machine learning method, by combining two Adaptive neuro-fuzzy inference systems (ANFIS) with sub clustering optimization (ANFIS-SC) and grid partitioning optimization (ANFIS-GP). The models are developed using meteorological data consisting of a maximum temperature, minimum temperature, and mean temperature as predictors. Three different scenarios were considered. The performance of the models is evaluated using the correlation coefficient (R), determination coefficient (DC), mean-squared error (MSE), root-mean-squared error (RMSE) and mean-absolute error (MAE). The simulation results indicated that the ANFIS ensemble (ANFIS-ENS) outperformed the individual ANFIS models. , Furthermore the overall performance of the ANFIS-ENS with three inputs, has the highest accuracy, with training$R = 0.9769$, DC= 0.9543, and testing$R = 0.9711, DC = 0.9430$, a training *MSE=0.0199, RMSE=0.1412*, *MAE=0.1014* and testing *MSE=0.0198, RMSE=0.1408, MAE=0.1038*. The developed models can be reliably used as alternative tool for estimation of solar radiation in Kano.

Keywords: Ensemble Machine Learning · ANFIS · Solar radiation · modeling · Kano-Nigeria

1. Introduction

Renewable energy sources like biomass, solar, water, geothermal, and wind are inexhaustible and ubiquitous. The key benefit in utilizing these energy sources is attributed to the fact that they are clean and does not pollute the environment with harmful gases (such as carbon mono-oxide) emission[1]–[3]. Solar energy, which is obtained from the sun, produces huge electrical energy which when harness effectively, may replace the need for any other electric energy source. The usage of solar energy in different parts of the world is increasing exponentially, due to continuous invention of solar energy dependent technologies. An application of solar energy systems includes electric power supply, water supply, agriculture, transportation, home appliances to mention some few. In reality, solar energy-based devices and power systems can now be considered a viable replacement for traditional energy-dependent systems in order to provide and preserve energy security worldwide [4], [5].

Even so, despite substantial attempts to use solar energy by numerous technical developments, its ability is still largely unexploited by both government as well as business firms until today. Since solar radiation affected by the geographical locations, in order to develop and deploy an optimal solar system; accurate, comprehensive and qualitative information and evaluation of solar radiation is needed [5]. Meanwhile, for the effective modelling, operation, and control of solar energy devices, reliable data on the available solar radiation is of great importance[6].

Solar radiation can be measured directly by installing instruments such as pyronometer and pyrheliometer or indirectly through measurement of sunshine hours and temperatures. In certain areas, particularly the developing nations, such as Nigeria, measurements and recording of solar radiation is quite challenging and complex because of the cost of purchasing these measurement instruments and their maintenance couple with calibration [7]. Hence, the solar radiation data is limited in these locations. In this regard, information on the solar radiation in those regions is estimated using various computational models and techniques, and the precise knowledge of the relationship between meteorological variables and solar radiation. Some literature uncovers that temperature, precipitation, wind speed and relative humidity, can indirectly provide a reasonable estimate of solar radiation[8], [9].

In this regard several empirical formulas have been suggested using temperature and sunshine hours as predictors[10], [11]. But although empirical models provide a number of advantages, one of them is computational simplicity. However, because these models are typically linear, they frequently produce unsatisfactory results when dealing with nonlinearity, and they also necessitate a big dataset for good estimation.

In order to enhance the capabilities of the predictive models and provide an option to empirical approaches, leaning based algorithms, like support vector regression (SVR), support vector machine (SVM), artificial neural-network (ANN), fuzzy logic inference systems, adaptive neuro-fuzzy inference systems (ANFIS) and random forest (RF) have been used in the literature[12]–[16]. These models are versatile, accurate, and are capable of handling nonlinear systems and small data. Conversely, learning-based models, while vastly superior to traditional empirical models, suffer from the general shortcomings of overfitting, local minima, and generalization, and often provide unsatisfactory results when used as stand-alone.

Recent soft computing and computational methods research has produced an advanced strategy that combines individual machine learning models in an ensemble form to complement one another. In a variety of modeling applications, ensemble machine learning techniques have proven to be effective[17]–[21]. As a result, the proposed research would look at using the ensemble method to estimate solar radiation.

This paper introduces an ANFIS ensemble method to predict the solar radiation, by combining two ANFIS architecture with grid Partition (GP) optimization and subtractive clustering (SC) optimization, in ensemble form. The performance of the three models is compared with each other, and furthermore, the results are further validated against the state-of-the-art studies on solar radiation prediction.

2. Material and Method

The overall study procedure is illustrated in the flow chart, shown in Figure1. The proposed method introduced three ANFIS models; the first model is trained using grid partitioning optimization method (ANFIS-GP) and the second using sub clustering optimization (ANFIS-SC). To harness the advantages of the two optimization techniques, the third model is built by combining them in an ensemble form (ANFIS-ENS). The data collection and preprocessing, as well as the performance evaluation procedure are described in the subsequent subsections.

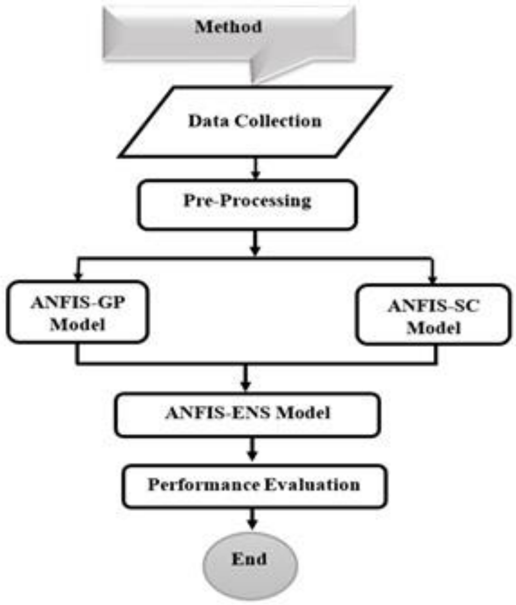

Figure 1. Proposed Methodology

2.1. Data Collection and Preprocessing

In this study, the model uses data set of daily solar radiation parameters for the time period of 12 months in the year 2018(starting from January to December). The parameters include maximum temperature (T_{max}), minimum temperature (T_{min}), average temperature (T) and solar radiations (st, st-1, st-2). Kano has latitude of $12^0$03'N, longitude of $12^0$32'E and an altitude of 472m. The study area has a mean height of around 472.45m atop sea level. The data is obtained from Nigerian Meteorological Agency (NIMET). The original data contained average temperature (T), maximum temperature (T_{max}), minimum temperature (T_{min}), precipitation (R), wind speed (WS), relative humidity (RH) and the solar radiation (SR). The correlation between the parameters is checked to select those parameters with correlation greater than or equal to 50%. This is to avoid using too much parameter that does not influence the output. Figure 2 shows the correlation matrix. It can be observed that the var7, which represents the solar radiation, is highly correlated with first three variables, var1, var2 and var3, representing the mean, maximum and minimum temperatures, respectively. Therefore, only the three variables are selected for the modeling.

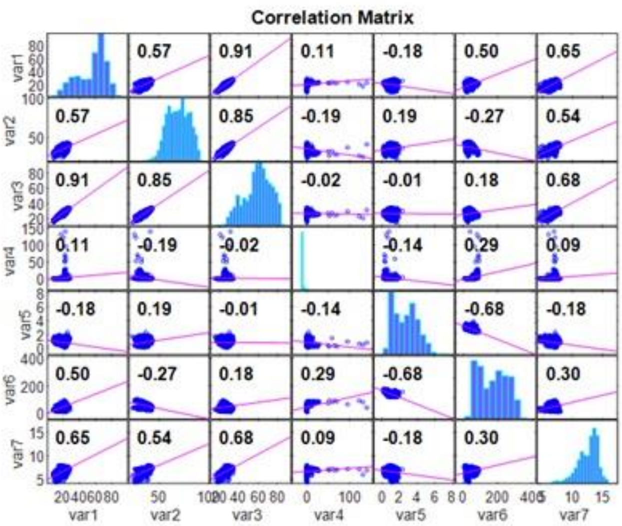

Figure 2. Correlation Matrix

In this respect three different models are proposed. The first model M1 uses mean, maximum and minimum temperatures as predictors. The second model M2, included as predictor, the solar radiation data from the previous day along with the temperatures. While the third model used solar radiation data from the previous two days as predictors, along with the temperatures. These are expressed mathematically as follows:

$$M1 = SR_k(T, Tmax, Tmin) \quad (1)$$

$$M2 = SR_k(T, Tmax, Tmin, SR_{k-1}) \quad (2)$$

$$M3 = SR_k(T, Tmax, Tmin, SR_{k-1}, SR_{k-2}) \quad (3)$$

2.2 Adaptive Neuro Fuzzy Inference System (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) is defined as a combination of fuzzy system and the learning ability of neural networks [22]. There are three main types of ANFIS, Mamdani, Sugeno, and Tsumoto. While the Sugeon's system is the most used[23]–[25]. In Fuzzy logic, inputs data is converted into fuzzy values by employing membership functions. Fuzzy values are comprised between 0 and 1. Nodes which working as membership functions (MFs) and rules permitting to model the relationship between input and output, form the structure of the ANFIS model. Several types of Membership Function exist including triangular, trapezoidal, Gaussian and sigmoid. The Gaussian function shown in Equation 4 below is the most commonly used MF[26].

$$V_{Li} = \frac{1}{1+[{}^{(X-\alpha i)}/_{\beta i}]^{2\mu i}} \quad (4)$$

The variable x is the input at i node, V_{Li} is the membership function, while βi and μi are the conditional parameters of the function. For ANFIS, rules are described according to their antecedents (if part) and consequents (Then part) and these rules are stored in a fuzzy based rule system ('the IF-THEN' rules). Equation 5 and 6 show the rules for a sugeno ANFIS model having two inputs (a and b) and one output f [27]

$$Rule\ 1; If\ x\ is\ P_1\ and\ y\ is\ Q_1, then\ f_1 = P_1x + q_1y + r_1 \quad (5)$$

$$Rule\ 2; If\ x\ is\ P_2\ and\ y\ is\ Q_2\ then\ f_2 = P_2x + q_2x + r_2 \quad (6)$$

Where P_1, P_2, Q_1 and Q_2 are called fuzzy sets, while f_1, f_2 are the output within the fuzzy region, and r_1, r_2 represent design parameters obtained during the training process. Figure 3a illustrates the architecture of an ANFIS having two inputs viz; x and y and only one output i.e.; f. Mature et all [28]details an extensive study on ANFIS.

The objective function as shown in figure 3b is minimized prior to calculating new fuzzy clusters. P which is the comprise o and 1, is the fuzzifier exponent, while c is the number of clusters, N is the number of data points and a, is the cluster centers.

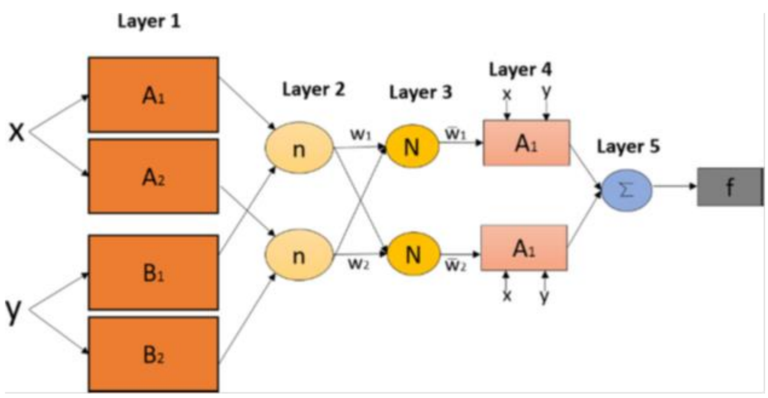

Figure 3a**.** ANFIS structure with two inputs, one output and two rules [29]

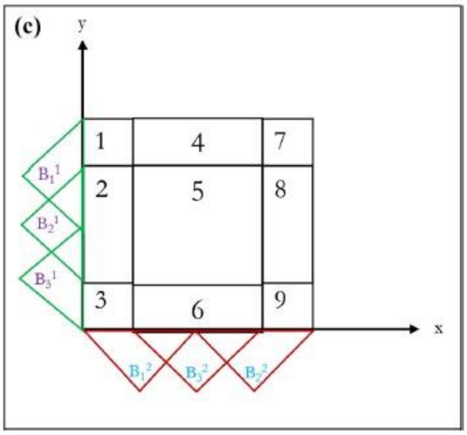

Figure 3b. Grid partitioning having 2 inputs with k=3 [30]

2.2.1 Grid Partitioning (GP)

ANFIS and grid partition are combined to form ANFIS-GP. For grid partition method, data is split in to smaller sized problem called grid data. According to the type of membership function (MFS) in every dimension a chart description of ANFIS-GP having three partitions (k=3) was presented as shown in Figure 3b. ANFIS-GP starts with zero output and gradually learns distinctive fuzzy set rules and functions by training procedure [31]. To determine the initial fuzzy sets and parameters, the least square method is employed according to partitions and MF types [32]

2.2.2 Subtractive Clustering (SC)

ANFIS and SC are merged to form ANFIS-SC. Every single data set is regarded as a potential cluster center. Consequently, a point with multiple neighboring points displayed a high potential value. Therefore, in pursuance of determining the first cluster center, a measure of density (d_i) is outlined in equation (4) below and the first cluster center was elected as the data set point with the highest density or potential value[31].

$$d_i = \sum_{K=1}^{N} exp\left(-\left(\frac{2}{r_0}\right)^2 .\ \|x_i - x_k\|^2\right) \quad (7)$$

Where $x_i$is considered cluster center, x_k is the remaining data points and r is the influence radius thereafter chosen the first cluster center. Equation 8 below is used to compute the new density measurement[33] .

$$d_{inew} = d_i - d_1' . exp\left(-\frac{\left(-\|x_i - x_1'\|^2\right)}{\left(\frac{r_b}{2}\right)^2}\right) \quad (8)$$

r_b Is constant expressing the neighborhood which will have computable decreasing in potential. The immediate point after the first cluster center will decrease significantly and is less likely to be chosen's subsequent cluster center. The choice of the influential radius is essential for determining the number of clusters, the choice of influential radius is essential. Optimal r_a must be between 0.1 and 2[33] and r_a is equal to 1.25r_b [34]. The higher the clusters the more rules will be developed. Hence, it is primitive to get around very small radius.

2.3 Ensemble Machine Learning

The single models, based on their robustness and constraints, provide varying levels of accuracy, which is often unsatisfactory. As a result, ensemble machine learning is used in a variety of fields, including science, engineering, social and management sciences, and health sciences, among others. Ensemble techniques are a type of machine learning that deals with heterogeneous and homogeneous models in combination[35].

By integrating their individual outputs as new input variables, the ensemble technique is employed to improve the simple models' final performance skills. Several studies have shown that Ensemble approaches are more reliable than simple models in solving complicated problems.

2.4 Performance Evaluation

The performance of the models during both the training and testing is evaluated by using four widely used statistical metrics: the correlation coefficient (R), determination-coefficient(DC), mean-squared-error (MSE) root-mean-squared-error (RMSE) and mean absolute error (MAE). They can be computed using Equations (9-13). [36]–[38]

$$\boldsymbol{R} = \frac{\sum x_i - \hat{x}_i}{n} \quad (9)$$

$$\boldsymbol{DC} = 1 - \frac{\sum(x_i - \hat{x}_i)^2}{\sum(x_i - \bar{x}_i)^2} \quad (10)$$

$$\boldsymbol{MSE} = \frac{\sum(x_i - \hat{x}_i)^2}{n} \quad (11)$$

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum(x_i - \hat{x}_i)^2}{n}} \quad (12)$$

$$\boldsymbol{MAE} = \frac{1}{n}\sum|x_i - \hat{x}_i| \quad (13)$$

For $i = 1,2,3 \ldots \ldots .. n$

Wherex_i, $\hat{x}_i$, $\bar{x}_i$ and n stands for the original values, predicted values, an average value of the original data and the total number of data instances. $\boldsymbol{R}$ And $\boldsymbol{DC}$ take values between 0 and 1, with 1 indicating a perfect prediction. The small values of ***MSE, RMSE*** and ***MAE*** show good performance of the models.

3. Results and Discussion

Table 1 indicates high coefficient of determination (DC) ranging from 78% to 98% which is highly commendable for predictive model. The independent variables are RH, WS, Tmin, Tmax and T. However, the correlation matrix between SR and each of the inputs indicates there is a strong and positive correlation between SR and Tmin, Tmax and T, hence a model of SR with these temperatures have been developed. Three input combinations constitute a model M1, M2 and M3. The statistical indicators (DC, RMSE, DC, MSE and MAE) as shown in Table 1 are used to outline the accuracy of the model. For each of M1, M2 and M3 the performance of ANFIS-GP, ANFIS-SC and the combination of the two (ensemble) have been evaluated. 80% of the data is used for training whilst the remaining 20% is used for testing.

The performance of the models is expressed using various statistical metrics as discussed, to check both the goodness of fit and performance error. The performance comparison results for the models are shown in Table 1. It is evidently observed from this table that all the three models could give a considerably accurate prediction of the solar radiation. Among the single models, the model M3 express higher performance in comparison to the M1 and M2 since it has the highest value of the DC (0.954294, 0.943043) and lowest values of RMSE (0.14123, 0.140843) in the training and testing phases.

Moreover, the results have shown the advantage of using the Ensemble techniques, since for each of the three models M1, M2 and M3 ensemble method provide higher accuracy than the individual SC and GP.

Table1. Performance evaluation of the models

	TRAINING					
	Methods	**R**	**DC**	**MSE**	**RMSE**	**MAE**
M1	**GP**	0.804458	0.647153	0.153991	0.392417	0.281549
	SC	0.777725	0.604856	0.17245	0.415271	0.301986
	ENS	**0.915535**	**0.838204**	**0.070612**	**0.265729**	**0.192211**
M2	**GP**	0.897626	0.805733	0.084783	0.291174	0.205587
	SC	0.834153	0.695812	0.132755	0.364355	0.262664
	ENS	**0.949031**	**0.900659**	**0.043355**	**0.208218**	**0.149999**
M3	**GP**	0.964419	0.930103	0.030505	0.174656	0.119767
	SC	0.898913	0.808045	0.083774	0.289437	0.203251
	ENS	**0.97688**	**0.954294**	**0.019947**	**0.141235**	**0.101438**
	TESTING					
	Methods	**R**	**DC**	**MSE**	**RMSE**	**MAE**
M1	**GP**	0.734001	0.538758	0.160639	0.400798	0.29424
	SC	0.70589	0.498281	0.174736	0.418014	0.301246
	ENS	**0.889518**	**0.791242**	**0.072705**	**0.269639**	**0.195615**
M2	**GP**	0.878747	0.772197	0.079338	0.28167	0.204257
	SC	0.777636	0.604718	0.137666	0.371034	0.262925
	ENS	**0.936985**	**0.877941**	**0.04251**	**0.20618**	**0.150755**
M3	**GP**	0.959621	0.920873	0.027558	0.166006	0.11559
	SC	0.863194	0.745104	0.088774	0.297949	0.211935
	ENS	**0.971104**	**0.943043**	**0.019837**	**0.140843**	**0.103832**

For more clarity the comparative analysis of the predictive model's performance error, in terms of the RMSE can be illustrated pictorially using bar chart. As shown in Figure 4, for all training algorithm for model M1, the RMSE is within the acceptable range during the training as well as the testing stages. This re-affirms the ability of the models to capture the complex relationship between the predictors and the solar radiation very well especially in the case of NFE.

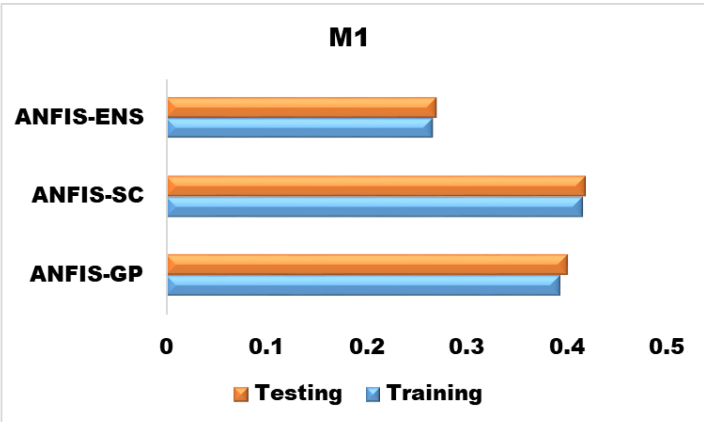

Figure 4. Performance comparison of model M1

The radar chart for model M2 is shown in figure.5, the comparative predictive result for M2 as given in Table1. From the table it is observed that the ENS model is the best with DC of 0.900659, 0.877941 for training and testing respectively, and RMSE of 0.208218 and 0.20618 for training and testing respectively.

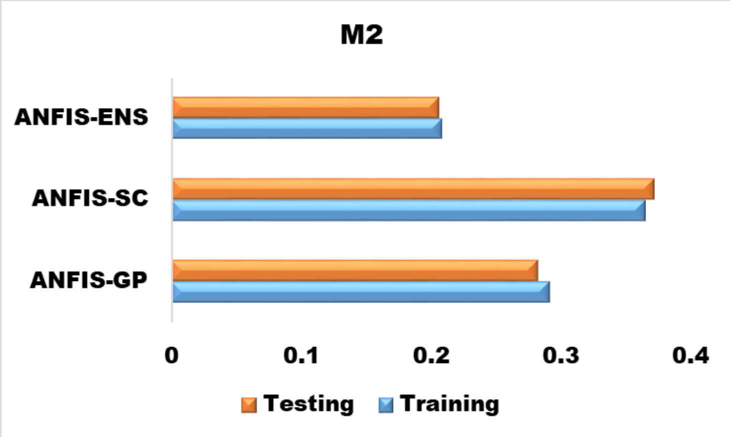

Figure 5. Performance comparison of model M2

Figure 6 and Figure 7 described the graphical representation of model's performance in bar chart and radar chart respectively. The performance ranking of the models in M1 is similar to M2 in both training and testing as $ENS > GP > SC$.

Similarly, for model M3 ensemble method outperforms SC and GP method having a DC, RMSE of (0.954294, 0.943043) and (0.141235, 0.140843) for training and testing respectively.

The pictorial representation of the model M3 are shown Figure 6 and Figure 7 bar chart and radar chart respectively.

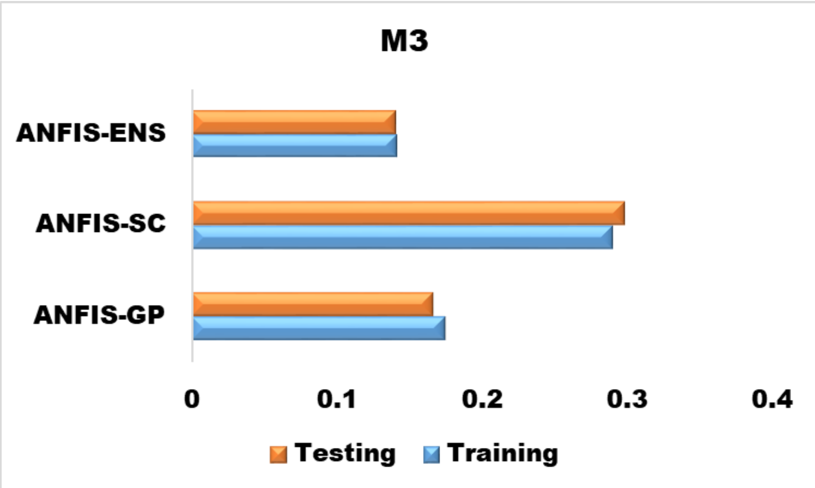

Figure 6. Performance comparison of model M3

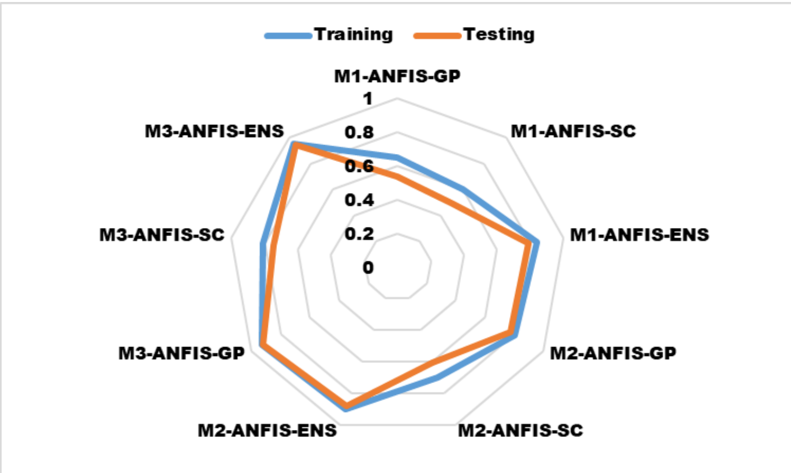

Figure 7. Radar Plot to compare the performance of the Models

The radar chart in Figure 7 provides a clear view of the comparison of the models M1, M2 and M3 based on the coefficient of determination (R^2). The models with their DC values closer to 1 generally have more accuracy. Hence, the order of accuracy of the three models developed can be rank in terms of accuracy from highest to lowest as $ENS > GP > SC$.

3.1 Model Validation

The Ensemble model developed was validated by examining in contrast the results obtained with [39]. To compare the accuracy of the developed model DC is used for performance evaluation. The result obtained by other researchers using different locations and different models is shown in Table 2. The developed model clearly shows superior performance in comparison with other developed models on account of DC values obtained.

Table 2 Comparison between the present study and the previous studies available from the literature

Authors	Model Type	Input Parameters	Location	DC Values
Yohanna et al[10]	Empirical	3	Nigeria	0.608
Abdalla [40]	Empirical	4	Bahrain	0.780
Ramedani [41]	ANFIS	3	Iran	0.808
Olatomiwa et al [8]	ANFIS	3	Nigeria	0.8544
Sajid and Ali[14]	ANFIS	3	Abu Dhabi	0.860
Sani S et al [7]	ANFIS	4	Nigeria	0.8688
Present Study	ANFIS ENSEMBLE	3	Nigeria	0.9543

4. Conclusion:

In this work, the application of ensemble machine learning algorithm for the prediction of solar radiation has been investigated. The main research aim is to developed robust machine learning models for the estimation of solar radiation in Kano-Nigeria. The meteorological data with four parameters including: Maximum-Temperature (Tmax), Minimum-Temperature (Tmin), Mean-Temperature (Tmean), along with the solar radiation is used. The data comprises of daily average values for the time span of ten (12) months (January-December, 2018). The study combined the two optimization techniques sub-clustering and grid-partitioning methods to form an ensemble model. The results obtained from the simulation and the prediction performance was access by using "R, DC, MSE, RMSE and MAE" metrics. Multiple performance metrics were employed in order to avoid bias and have better generalization of the accuracy. As a result of the findings, we may conclude that using the ensemble approach produces more credible and acceptable outcomes.

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