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Short Term Solar Radiation Forecast from Meteorological Data using Artificial Neural Network for Yola, Nigeria

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ABSTRACT: *Short term forecast for solar radiation using Artificial Neural Networks has been designed for Yola. Twelve months hourly data were used and two distinct ANNs (ANN_1 and ANN_2) were employed. ANN_1 was applied to the time series of solar radiation data alone to forecast future solar radiation; and wind speed, wind direction, ambient temperature, relative humidity and barometric pressure were used as inputs to ANN_2 to obtain forecast for the same solar radiation. The results for the ANN_1 and ANN_2 models forecasts of the 1 to 6 hr ahead solar radiation with respect to their performance evaluation have shown that the maximum values of MAE, RMSE and MRE were 49.93, 63.20 and 0.194 respectively for ANN_1; and 159.00, 177.21 and 0.582 respectively for ANN_2. The coefficient that determines the strength of their correlation with the observed data (R^2) were found to be 0.992 for ANN_1 and 0.939 for ANN_2 hence ANN_1 is tentatively a better solar radiation forecasting model for Yola.*

Keywords: *Solar Radiation, Artificial Neural Network, Forecast, Meteorological Data, Short Term, Yola*

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I. INTRODUCTION

The knowledge of the variability of solar radiation is a key to determining the designs of solar energy devices for optimum performance. For PV operators, it mellows down the challenges faced in forecasting solar power and delivery management. Proper solar radiation forecasts help to strategize against incurring unseen additional costs and to provide power supply that is stable and secured. For future solar electricity market to succeed, systematic modeling for short term forecast for solar radiation may be necessary.

Artificial Neural Networks (ANNs) has been found suitable for short-term solar radiation forecasting. Artificial Neural Networks (ANN) are structures inspired by the natural intelligence and the human ability to adapt its way of thinking to complex problems, in its learning form experience and generalizing capabilities. These structures are nonlinear data-driven capable of performing nonlinear modeling without a priori knowledge about the relationship between input and output variables. Thus, they are a powerful, general and flexible modeling tool for forecasting purposes [1].

Several other methods based on time series for forecasting solar radiation in different time scales have appeared recently: Fuzzy Logic (FL) and hybrid system such as Adaptive Neuro Fuzzy Interface System (ANFIS), ANN-wavelet, and ANN-genetic algorithms [2]. These approaches can be classified into three different types [3]; two of which are employed in this work, first estimating the solar irradiance (in different time scales) based on some meteorological parameters such as ambient temperature, relative humidity, wind speed, wind direction, cloud, sunshine duration, clearness index, pressure, etc. and geographical coordinates as latitude. The second approach allows predicting the future solar irradiance (in different time scales) based on the past observed data [4, 5, 6, 7, 8]. The two methods of approach highlighted has been used and compared for Yola.

II. MATERIALS AND METHODS

2.1 Data

A twelve months (366 days) secondary weather data from November, 2011 to November, 2012 of solar radiation, ambient temperature, wind speed, wind direction, relative humidity and barometric pressure recorded at 5 min intervals from Nigerian Environmental Climate Observation Program (NECOP) installed at Modibbo Adama University Technology, Yola, Adamawa State were used in this study. The original data were converted to hourly steps using Microsoft Excel. Yola is the capital city and administrative center of Adamawa State, Nigeria, with a land area of 923,768 km^2, located at an elevation of about 180 m, it lies on the geographical coordinates of Latitude 9° 12′ 30″ N and Longitude 12° 28′ 53″ E.

2.2 Basic Theory of Artificial Neural Network

At a time instant t, a k-step ahead solar radiation is predicted as the average solar radiation, and the number of hours ahead a forecast is needed is called the forecast horizon, H. For example, given hourly solar radiation data, an hour-ahead solar radiation forecast means to predict solar radiation at time t + 1 as the average solar radiation during the 1 hour after time instant t. If this procedure is carried out for 24 hours, then the forecast horizon is 24 h. The choice of k and H depends on the motivation for the prediction. In the real time (RT) stage of power system operations, k is 5 min to 10 min, and the forecast horizon can be 24 h [9].

The multilayer perceptron is a static feed-forward network typically trained with a supervised learning process and one of the most applied to solar forecasting. The basic operation of a multilayer perceptron network unit is such that the output *o* of a node is the image of the weighted sum of all its inputs *i* by some activation function *f* (Equation 1). The activation functions employed in a multilayer perceptron can be linear, log-sigmoid or tan-sigmoid [10].

$$o = f\left(\sum_j w_j i_j + b\right) \quad (1)$$

During the network training the weights *w* and the bias *b* were adjusted for each unit using the back propagation algorithm. The back propagation algorithm is a gradient-descent based algorithm that seeks to minimize the prediction error *E* of the network in the training data by propagating back the error signal through input.

$$E = \sum_i \|o_i - \hat{o}_i\|^2 \quad (2)$$

Two distinct ANNs (ANN_1 and ANN_2) were employed in this work. First, ANN_1 was applied to the time series of solar radiation data alone to forecast future solar radiation and second, wind speed, wind direction, ambient temperature, relative humidity and barometric pressure data were used as inputs to ANN_2 in obtaining forecasts for the same solar radiation. The results of ANN_1 and ANN_2 were then compared.

2.3 ANN_1 and ANN_2 Designs

The ANN_1 is a time series model whose network structure was determined from the knowledge of the number of its inputs which in turn given by the number of lags after trial and error minimization. The best model and its parameters were picked from these trials. Based on minimum errors, the selected network was severally tried on varying number of hidden layers, neurons and activation functions (sigmoid or hyperbolic tangent) to make forecasts of 1h to 6h ahead after which the best of the combinations was chosen. The number of input nodes of ANN_1 corresponds to the number of past observations of the solar radiation that contain relevant information to explain the value to be predicted (the current value). The first four past values of the solar radiation were the only ones containing relevant information to explain the current value of the solar radiation. The four most recent past values of the solar radiation therefore formed the four set of inputs that were required by the network. However, the ANN_2 though went through similar processes of selecting the best network but had the wind speed (WS), relative humidity (RH), ambient temperature (AT), wind direction (WD) and barometric pressure (BP) as inputs.

For normalized output and three neurons at the hidden layer 1 of ANN_1 and ANN_2 several trials were made to determine the best of each of the model architectures. The best model architectures along with their corresponding performances are summarized in Table I for ANN_1 and in Table II for ANN_2. The best model selected based on the least sum of squares error (SSE) in the testing sample is one with serial number 18 for ANN_1 and serial number 17 for ANN_2. ANN_1 has SSE value of 8.056 and RE value of 0.117 while ANN_2 has 19.080 and 0.281 for SSE and RE respectively.

The selected model for ANN_1 has one input layer, two hidden layers and one output layer; the input layer consists of four units (excluding the bias) and the first hidden layer has three units (excluding the bias), the second has two units (excluding bias) while the output layer contains a unit (Figure 1). Hyperbolic tangent activation function (standardized scaling) was used at the hidden layers while sigmoid activation function (normalized scaling) was employed at the output layers while gradient descent algorithm and batch type training were applied to the network.

Table I: Sample of Models Tried, Training Performance and Testing for ANN_1 Design

Model	Rescaling Input	No. of nits H2	Activation Hidden	Activation Output	Training (SSE)	Training (RE)	Training time	Testing SSE	RE
1	AN	2	Hyp. tan	Sigmoid	21.172	0.126	0:00:00:48	8.483	0.117
2	AN	2	Hyp. tan	Sigmoid	23.211	0.136	0:00:00:28	8.499	0.120
3	AN	2	Sigmoid	Sigmoid	21.423	0.129	0:00:00:36	9.849	0.132
4	AN	2	Sigmoid	Sigmoid	22.603	0.136	0:00:00:28	8.835	0.119
5	AN	-	Sigmoid	Sigmoid	21.396	0.129	0:00:00:23	9.281	0.123
6	AN	-	Sigmoid	Sigmoid	23.976	0.142	0:00:00:17	9.747	0.135
7	AN	-	Sigmoid	Sigmoid	21.867	0.132	0:00:00:17	9.990	0.133
8	N	2	Sigmoid	Sigmoid	23.017	0.137	0:00:00:30	10.879	0.149
9	N	2	Sigmoid	Sigmoid	22.973	0.136	0:00:00:31	10.028	0.138
10	AN	2	Hyp. tan	Sigmoid	20.823	0.124	0:00:01:00	9.181	0.122
11	AN	2	Hyp. tan	Sigmoid	21.527	0.125	0:00:00:52	8.998	0.125
12	AN	2	Hyp. tan	Sigmoid	25.928	0.131	0:00:00:47	10.372	0.120
13	STD	2	Hyp. tan	Sigmoid	20.123	0.121	0:00:00:55	10.229	0.136
14	STD	2	Hyp. tan	Sigmoid	24.951	0.124	0:00:00:39	10.841	0.130
15	STD	-	Hyp. tan	Sigmoid	21.531	0.128	0:00:00:16	10.125	0.135
16	STD	-	Hyp. tan	Sigmoid	21.234	0.126	0:00:00:30	8.902	0.122
17	STD	-	Hyp. tan	Sigmoid	22.375	0.122	0:00:00:27	10.663	0.134
18	STD	2	Hyp. tan	Sigmoid	23.003	0.134	0:00:00:36	8.056	0.117
19	STD	-	Hyp. tan	Sigmoid	20.515	0.122	0:00:00:36	8.202	0.113
20	STD	-	Hyp. tan	Sigmoid	21.977	0.128	0:00:00:19	8.495	0.122

*AD (Adjusted and Normalized), N (normalized) and STD (standardized)

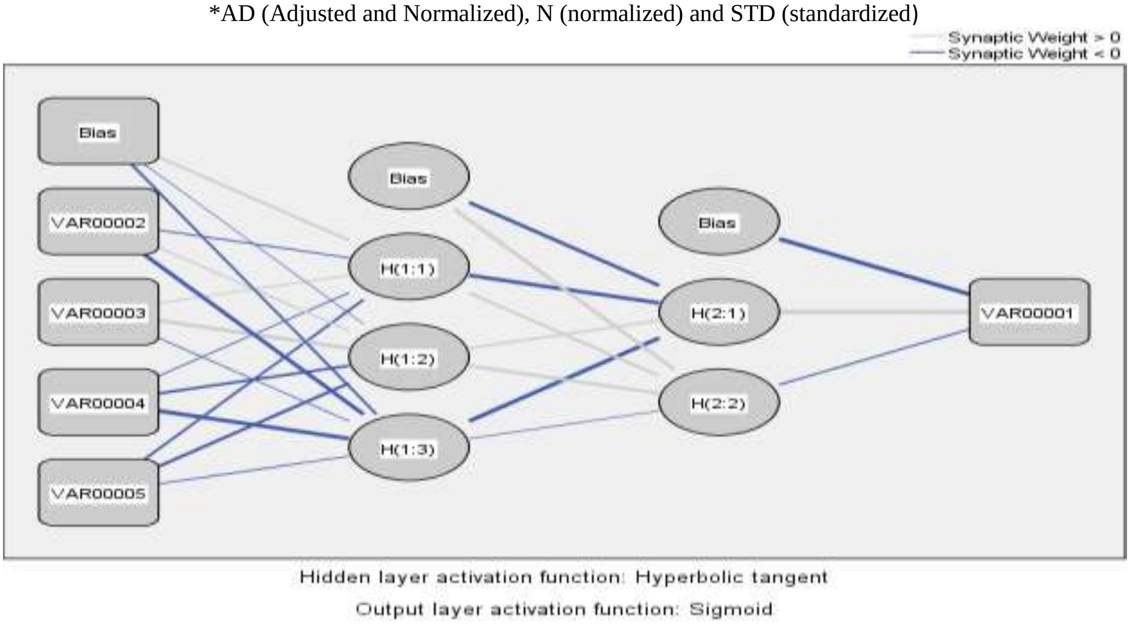

Figure 1: Architectural diagram of ANN_1

Table II: Sample of Models Tried for ANN_2 Design

Model	Rescaling Input	No. of units H2	Activation Hidden	Activation Output	Training (SSE)	Training (RE	Training Train	Testing SSE	Testing RE
1	AN	2	Hyp. tan	Sigmoid	47.758	0.288	0:00:00:47	19.286	0.256
2	N	-	Sigmoid	Sigmoid	49.376	0.290	0:00:00:30	19.738	0.279
3	AN	2	Sigmoid	Sigmoid	53.496	0.298	0:00:00:47	21.655	0.262
4	AN	2	Hyp. tan	Sigmoid	50.535	0.306	0:00:00:30	21.936	0.289
5	AN	-	Hyp. tan	Sigmoid	53.009	0.313	0:00:00:22	21.691	0.303
6	AN	2	Hyp. tan	Sigmoid	48.778	0.291	0:00:00:37	21.611	0.295
7	AN	-	Hyp. tan	Sigmoid	53.408	0.320	0:00:00:28	22.376	0.302
8	N	-	Sigmoid	Sigmoid	52.776	0.312	0:00:00:19	21.069	0.293
9	N	-	Sigmoid	Sigmoid	52.499	0.308	0:00:00:22	21.404	0.305
10	N	2	Sigmoid	Sigmoid	51.877	0.302	0:00:00:31	20.118	0.292
11	N	2	Sigmoid	Sigmoid	53.684	0.319	0:00:00:22	22.912	0.316
12	N	-	Sigmoid	Sigmoid	51.253	0.301	0:00:00:25	21.788	0.308
13	AN	-	Sigmoid	Sigmoid	56.002	0.325	0:00:00:14	22.361	0.316
14	AN	-	Hyp. tan	Sigmoid	51.562	0.283	0:00:00:22	23.214	0.290
15	AN	2	Hyp. tan	Sigmoid	53.121	0.316	0:00:00:37	22.459	0.308
16	AN	2	Hyp. tan	Sigmoid	51.205	0.278	0:00:00:42	22.994	0.294
17		-	Sigmoid	Sigmoid	50.249	0.290	0:00:00:22	19.080	0.281

Suppose $H_{(i:j)}$ stands for the hidden layers with $i = 1$ and $i = 2$ defining the first and second hidden layers respectively while the j stands for the particular unit of the hidden layer in the network. With hyperbolic tangent activation function at the hidden layers of ANN_1, $H_{(i:j)}$ can be written as:

$$H_{(i:j)} = tanhC_{(i:j)} = \frac{\exp C(i:j) - \exp - C(i:j)}{\exp C(i:j) + \exp - C(i:j)} \qquad (3)$$

where $C_{(i:j)}$ is the input combination (or weighted input) for the j^{th} unit of the i^{th} hidden layer of the network.

On the other hand, the selected model architecture for ANN_2 has one input layer, one hidden layer, and one output layer. The input layer has five units (excluding the bias), the hidden layer has three units (excluding the bias) and the output layer, a unit (Figure 2). Both the hidden and the output layers used sigmoid activation function.

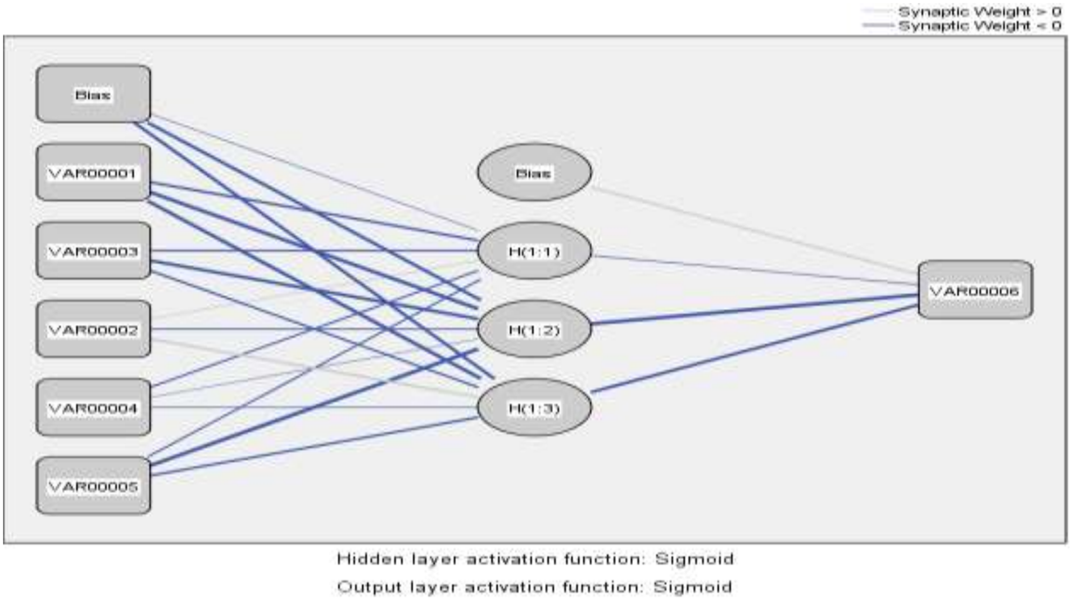

Figure 2: Architectural diagram of ANN_2

Adjusted normalized scaling was also used at its hidden layer and normalized scaling employed at its output layer. The network was similarly trained using gradient descent algorithm and the batch type training. Unlike ANN_1, it was the sigmoid activation function that was applied at the only hidden layer, $H_{(1:j)}$ and written as:

$$H_{(1:j)} = sigC_{(1:j)} = \frac{1}{1 + \exp[-C_{(1:j)}]} \qquad (4)$$

where $C_{(1:j)}$ is the input combination (or weighted input) for the j^{th} unit of the hidden layer of the network, given by:

$$C_{(1:j)} = w_{p,j}Y_{t-5} + w_{p,j}Y_{t-4} + w_{p,j}Y_{t-2} + w_{p,j}Y_{t-3} + w_{p,j}Y_{t-1} + b_{i,j} \qquad (5)$$

$w_{p,j}$ is the synaptic weight linking the p^{th} input unit to the hidden unit. $b_{1,j}$ is the bias corresponding to $C_{(1:j)}$. Y_{t-5}, Y_{t-4}, Y_{t-3}, Y_{t-2} and Y_{t-1} are the five input solar radiation values.

2.4 Parameter Estimates

The ANN_1 and ANN_2 parameters required for the forecasts of solar radiation from the best model architectures selected are presented in Tables III & IV. They contain the values of the weights and bias applied at different levels of operation of the networks during the forecast.

Table III: Parameter Estimates of ANN_1

Predictor		Predicted					
		Hidden layer1			Hidden layer2		Output layer
		H(1:1)	H(1:2)	H(1:3)	H(2:1)	H(2:2)	
Input layer	Bias	-0.355	-0.237	-0.580			
	lag2	-0.590	0.944	-1.254			
	lag3	0.111	0.284	-0.004			
	lag4	-0.296	-0.061	0.122			

	lag5	0.204	-0.846	0.203			
Hidden layer1	Bias				0.373	-1.009	
	H(1:1)				-1.014	-0.664	
	H(1:2)				0.930	0.666	
	H(1:3)				-1.105	0.056	
Hidden layer2	Bias						-1.669
	H(2:1)						1.897
	H(2:2)						1.311

Table IV: Parameter Estimates of ANN_2

Predictor		Predicted			
		Hidden layer1			Output layer
		H (1:1)	H (1:2)	H (1:3)	
Input layer	Bias	-0.330	-3.008	-1.781	
	VAR0001 (AT)	-1.256	-3.524	-3.176	
	VAR0002 (WS)	-0.838	-3.402	-0.895	
	VAR0003 (RH)	-0.618	-0.687	1.327	
	VAR0004 (WD)	-0.764	-0.030	-0.372	
	VAR0005 (BP)	-0.713	-4.432	-1.188	
Hidden layer1	Bias				1.177
	H (1:1)				-0.618
	H (1:2)				-5.199
	H (1:3)				-3.085

2.5 *Performance Evaluation*

The performance evaluation of the forecasting models was done in three steps: Firstly, the elements to be forecast were removed from the original time series, and the remaining series consisted in the training series. Secondly, the removed elements were predicted employing each of the models described. Thirdly, the evaluation criteria based on the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), and the Mean Relative Error (MRE) were employed. These criteria [3] are mathematically expressed as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Y_t - Y_t^*| \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Y_t - Y_t^*)^2}{N}} \tag{7}$$

$$MRE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_t - Y_t^*}{Y_t}\right| \tag{8}$$

where N is the number of data points, Y_t and Y_t^* are the observed and forecasts solar radiation values respectively, at time t.

III. RESULTS AND DISCUSSION

The plots of the observed solar radiation data and the corresponding sets of forecasts for six hours ahead from each of the ANN_1 and ANN_2 are presented in Figure 3 (a & b) and the corresponding 24 hr time horizon forecast in Figure 4. The trend line and the coefficient of determination (R^2) are display on each of the graphs.

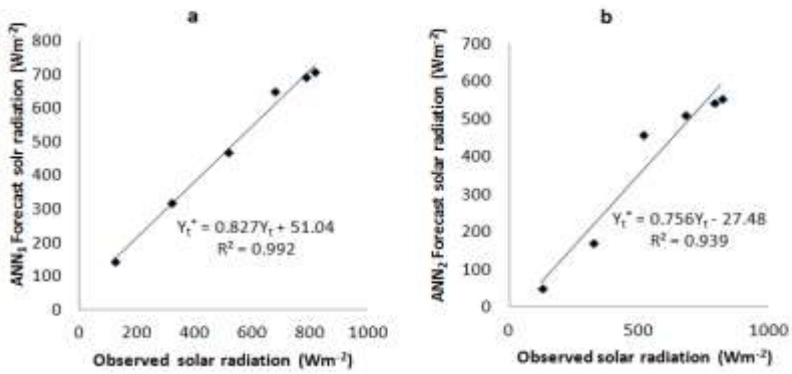

Figure 3 (a & b): Plots of 6 h ahead forecasts from ANN_1 and ANN_2 Models against observed values

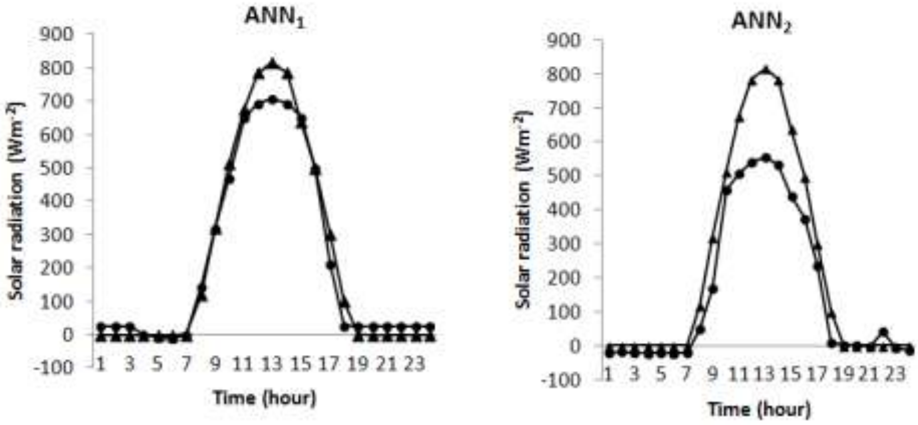

Figure 4: Plots of ANN_1 and ANN_2 solar radiation forecasts against observed values (Triangular markers) for 24 hour ahead

Table V gives the values of the evaluation criteria: the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), and the Mean Relative Error (MRE) respectively for ANN_1 and ANN_2 Models. These values were computed for one hour ahead through six hours ahead, using Equations (6, 7 & 8). It could be seen from the table that ANN_1 has lower values for all of the fitness parameters used than ANN_2.

Table V: Values of MAE, RMSE and MRE for ANN_1 and ANN_2

Time ahead	ANN_1			ANN_2		
(hr)	MAE	RMSE	MRE	MAE	RMSE	MRE
1	23.57	23.37	0.194	70.55	70.55	0.582
2	12.64	16.71	0.095	110.74	117.81	0.526
3	22.97	28.65	0.035	92.40	101.43	0.387
4	24.17	28.44	0.016	111.68	122.06	0.353
5	37.90	48.68	0.011	138.35	154.68	0.344
6	49.93	63.20	0.032	159.00	177.21	0.340

Therefore, the artificial neural network which forecasts the solar radiation using its four most recent previous values makes a better option for Yola. In terms of the correlation of the forecast and the observed solar radiation, Figure 3 shows that ANN_1 with R^2 value of 0.992 is better fitted to the observed values than ANN_2 which has R^2 value of 0.939. At the 24 hr time horizon (Figures 4), it is clearly observed that the solar radiation forecasts from ANN_1 fit the observed solar radiation data better than the forecasts from ANN_2 hence can be used for 1 to 6 hr forecast for Yola with better accuracy.

V. CONCLUSION

The artificial neural network denoted ANN_1 is found to be better of the two models designed in this study. It has four input nodes (containing the most recent previous solar radiation data), two hidden layers containing three and two neurons respectively and one output neuron (containing the solar radiation to be forecast). ANN_1 is capable of forecasting the 6h ahead solar radiation with maximum mean absolute error of 49.93, a maximum root mean squared error of 63.20 and a maximum mean relative error of 0.194. Hence ANN_1 may be considered as a tentative tool for short term solar radiation forecasting tool for Yola.

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