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DEVELOPMENT OF A NEURAL NETWORK MODEL FOR SOLAR RADIATIONESTIMATION IN KANO STATE NIGERIA

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ABSTRACT.

In this paper, the global solar radiation on the horizontal surface in Kano, Nigeria using 10-year data ranging from (2002-2012) was analysed based on the series of measured meteorological data: monthly mean (minimum temperature, maximum temperature, sunshine hours and relative humidity). Artificial Neural Network (ANN) was used to model the solar radiation. The ANN was fed with four input layers, monthly mean (minimum temperature, maximum temperature, sunshine hour and relative humidity) and one output layer (monthly mean solar radiation). 120 sets of data were used, 96 sets (80%) for training and 24 sets (20%) for testing.The root mean square error (RMSE), correlation coefficient(R), were used to assess the model performance. The results obtained indicates a good correlation between the measured and estimated result, the statistical parameters for the training phase are RSME= 0.9505MJ/m^2 and R= 0.92995MJ/m^2. This proves ANN soft computing technique as a good tool for solar radiation prediction.

Keywords:ANN, solar radiation, meteorological data, Kano, solar prediction

1.0 INTRODUCTION

Large integration of renewables into the future and existing energy supply structure has become mandatory due to fossil fuels depletion and fear of global warming. It has become necessary to explore renewable energy (RE) as alternative to our energy supply. Among the RE resources exploited across the globe, solar energy is the most exploited RE source due to its cleanliness and abundant availability. The availability of solar energy in Nigeria has been recognized as one of the most reliable and clean energy sources. It is free, environmentally friendly and available in abundant quantity [1]. Accurate understanding of solar radiation is key for every successful solar power project [2]. The understanding of solar radiation is required in order to have a proper solar energy forecast that will augment the load demand of the selected project area, it helps in projecting the amount of energy that could be generated at that particular area.

Although there are equipment designed for this particular purpose but are very costly and most countries cannot afford to buy them. It is also believed that most of these equipment are prone to instrumental hazard, high maintenance cost of the equipment has also contributed to non-patronage of the equipment [3]. Unavailability of the measurement equipment and other difficulties resulted in developing different algorithms and models for solar radiation prediction and estimation, the prediction and estimationare done using some of the measured weather data such as temperature, sunshine duration, relative humidity and clearness index etc[4].Nigeria has only few meteorological stations across the country and all these stations are government owned stations, mostof these stations have no solar radiation datarecord and sometimes with fewer or no records on other weather data.

Several works have been done to predict solar radiation prediction in Nigeria and other parts of the world. Empirical models were used to predict solar radiation in Nigeria by [5-8]. Also [9, 10] employed the use of artificial intelligence for solar radiation prediction using meteorological data. Further researches have also been carried out across the globe using artificial intelligence technique for solar radiation prediction [2, 11-16]. The works carried out proved the efficiency and accuracy of solar radiation prediction using artificial intelligence. The artificial Intelligence model employed for this research is artificial neural network (ANN). ANN is a mathematical model that executes a computational simulation of the behaviour of neurons in the human brain, by replacing the brains configuration to yield results based on learning of set of training data, they are generally referred to as intelligent systems that behave like human brains.

ANN has been utilized by many researchers for solar radiation prediction. The authors in[17] developed six ANN models for solar radiation estimation in Saudi Arabia, different combinations of inputs were utilized in the study which includes sunshine hours, air temperature and relative humidity. The results from the combination of sunshine hours and air temperature produced the best accuracy. [18] used ANN for solar radiation prediction and the results obtained was compared with empirical models. The developed ANN model outperforms the empirical models. Also [19] developed an ANN model to estimate solar radiation in China and the model developed was compared with empirical models. The developed model was found to have more correlation with the measured data than the empirical models, hence outperforms the empirical models. [20] developed and optimized ANN by optimizing the ANN with particle swarm optimization (ANN-PSO) for solar radiation prediction in Saudi Arabia,and was compared with a back propagation NN (BP-NN). The ANN-PSO outperformed the BP-NN model. ANN has been utilized for solar radiation prediction or estimation and has been proved to be a very good tool for solar radiation estimation.

In this study, ANN is used to investigate its suitability for solar radiation prediction on the horizontal surface in Kano state, Nigeria. Ten years data (2003-2012) was obtained from Nigerian Meteorological Agency (NIMET) to serve as input and output to the model for both the training and testing stage. The meteorological data used as inputs to the model are monthly mean sunshine hours, monthly mean minimum temperature, monthly mean maximum temperature and relative humidity while monthly mean solar radiation serves as the output to the model. The meteorological data chosen for this study is due to their strong correlation with solar radiation and their availability in the study area. The main objective of the study is to investigate the suitability of ANN model for solar radiation prediction in Kano, Nigeria.

2.0 Materials and methods

2.1 Study location

In this study, long term monthly average temperature (minimum, maximum and average), relative humidity and global solar radiation for a period of 11 years (2002-2012) obtained from Nigerian Meteorological agency (NIMET), Kano, Nigeria were utilized [21]. The data was recorded at Kano meteorological station in North West Nigeria at 12.0022°N longitude and 8.952°E latitude, at an altitude of 456m. The monthly mean average solar radiation of the site was obtained from National Aeronautics and Space Administration (NASA) website [22]. The monthly average data used for thisstudy were divided into two data sets, one set which is 80% of the data (2002-2009) was used for training while the other set which is 20% of the data (2010-2012) was used for testing.

2.2 Artificial Neural Network (ANN)

Artificial neural networks ANN are intelligent systems thatbehave like human brains, the neurons. Series of identical artificial neurons are connected together to form ANN, just like the brain. [23]defined ANN as a mathematical model that executes a computational simulation of the behaviour of neurons in the human brain, by replacing the brains configuration to yield results based on learning of set of training data. The most popular ANN architecture is the multilayer feed-forward network with a back-propagation learning algorithm. A typical ANN consist of three layers namely; input layer, output layer and the intermediate or hidden layer [24]. ANN consist of two stages for data manipulation, these stages are the training section and the testing section. The ANN model finishes the learning and storing of the pattern information of existing data base in the training section and recalls the information to produce output data based on particular input data base in the testing section. Fig.1 illustrates multilayer network with three layers mathematically expressed as:

$$Y = f(X, w) \qquad (1)$$

Where X= input vector,

Y= output vector and

$f(.)$ = Functional relationship between input vector and output vector

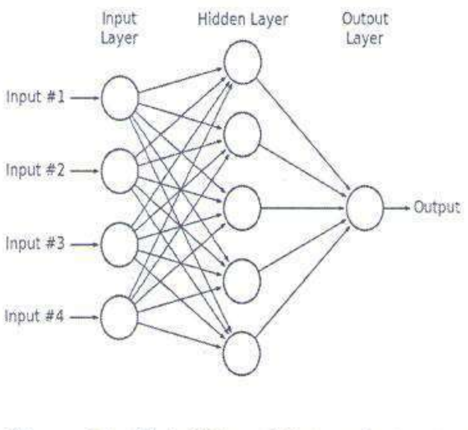

*Figure 1*Artificial Neural Network structure

Figure 2 illustrate the computational rule of a neuron, mathematically expressed as

$$Y = g(\sum_{i=1}^{n} w_i x_i) \qquad (2)$$

Where x_i= input parameters

w_i= weight for x_i

$g(.)$= the transfer function

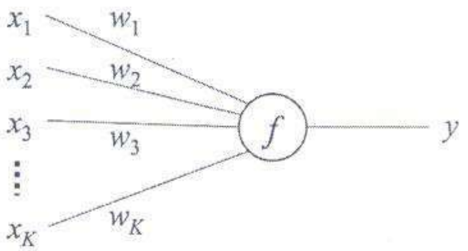

*Figure 2*Schematic diagram of the neuron unit

2.3 Model performance evaluation

The ANN model performance is analysed using the statistical indicators below

(1) Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \qquad (3)$$

(2) Coefficient of determination (R^2)

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - \overline{O_i})^2.(P_i - \overline{P_i})}{\sum_{i=1}^{n}(O_i - \overline{O_i}).\sum_{i=1}^{n}(P_i - \overline{P_i})} \qquad (4)$$

where O_i and P_i are predicted and experimental values respectfully, and $\overline{O}_i$ and $\overline{P}_i$ are average values of O_i and P_i respectively. Also n represents the number of test data. When higher value of is obtained, it shows that the model has a better performance while RMSE with smaller value indicates better performance of the model.

3.0 Result and Discussion

In this study, ANN is evaluated for solar radiation estimation. The estimation was computed using ten years meteorological data (2003-2012) from NIMET Nigeria (see APPENDIX A). 120 sets of data was used, 96 set (80%) for training and 24 sets (20%) for testing. Monthly mean sunshine hours, monthly mean minimum temperature, monthly mean maximum temperatureand monthly mean relative humidityserved as input to the developed ANN model. although the inputs are variable, the solar radiation served as output to the model. the precision of the developed model is assessed using two statistical indicators, the RMSE and R. lower values of RMSE signifies good correlation, though the ideal value is 0. R ranges between -1 and +1, the value of R near -1 or +1 signifies accuracy and perfect linear relationship between the target and measured values. If R nears 0 it illustrates non-linear relationship between estimated and target output.

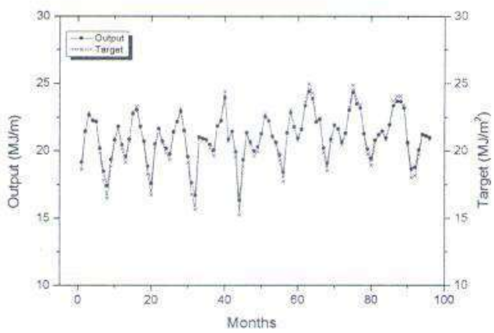

*Figure 3a*Training data (target and measured output).

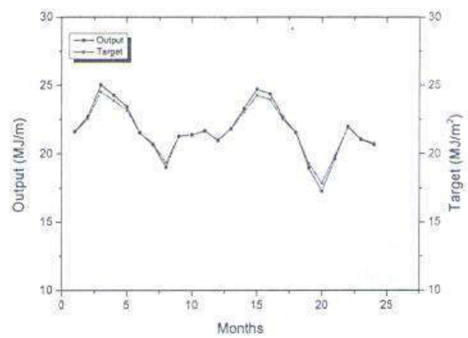

*Figure 3b*Testing data (target and measured output)

From table 1 the values of RMSE is very low (0.9505) and that of R (0.92995) is near 1, which signifies strong correlation and a perfect linear relationship between the measured and estimated solar radiation values. The estimated solar radiation is represented in Figure 3. Figure 3a represents the training data of the actual and estimated values, Figure 3b represents the testing data of the actual and estimated values, while 3c represnts all data i.e combination of training and testing data using the developed ANN model. from the figures represented, there is clear and strong correlation between the measured and estimated output which proves ANN to be a good model for solar radition estimation. From the plots, it is clear that the measured and estimated values have a very strong relationship.The study carried out proved ANN model to be capable of solar radiationestimation in Nigeria based on the meteorological data used. Hence proves ANN to have high potential for solar radiation estimation.

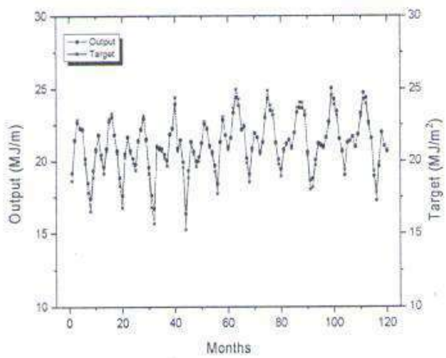

*Figure 3c*All data (target and measured output)

Table 1. Statistical performance evaluation of the ANFIS model

Data	RMSE	R
Training	0.9505	0.92995
Testing	1.6954	0.87969

4.0 Conclusion

Artificial Neural Network approach is proposed in this study for solar radiation estimation in Kano state Nigeria. Long term measured data of 10 years (2003-20012) was obtained from NIMET for Kano Nigeria. The study is aimed at investigating the feasibility of ANN for global solar radiation estimation in kano. Monthly mean sunshine hours, monthly mean (minimum temperature, maximum temperature and relative humdity) served as inputs to the ANN model while meauserd monthly mean solar radiation served as output of the model. The statistical indicators RMSE and R used for evaluating the model are 0.9505 and0.92995respectively, this signifies a very high correlation between the measured and estimated output. Based on these results, it is evident that that ANN is an efficient soft computing tool for solar radiation estimation. The developed model can be improved by adding more meteorological data to the model.

REFERENCES

1. Trabea, A. and M.M. Shaltout, *Correlation of global solar radiation with meteorological parameters over Egypt.* Renewable Energy, 2000. **21**(2): p. 297-308.
2. Chiteka, K. and C. Enweremadu, *Prediction of global horizontal solar irradiance in Zimbabwe using artificial neural networks.* Journal of Cleaner Production, 2016. **135**: p. 701-711.
3. Alam, M., et al., *Simulation of solar radiation system.* American Journal of Applied Sciences, 2005. **2**(4): p. 751-758.
4. Olatomiwa, L., et al., *Adaptive neuro-fuzzy approach for solar radiation prediction in Nigeria.* Renewable & Sustainable Energy Reviews, 2015. **51**: p. 1784-1791.
5. Ajayi, O., et al., *New model to estimate daily global solar radiation over Nigeria.* Sustainable Energy Technologies and Assessments, 2014. **5**: p. 28-36.
6. Fagbenle, R.L., *Total solar radiation estimates in Nigeria using a maximum-likelihood quadratic fit.* Renewable Energy, 1993. **3**(6-7): p. 813-817.
7. Falayi, E., J. Adepitan, and A. Rabiu, *Empirical models for the correlation of global solar radiation with meteorological data for Iseyin, Nigeria.* International Journal of Physical Sciences, 2008. **3**(9): p. 210-216.
8. Sambo, A., *Empirical models for the correlation of global solar radiation with meteorological data for northern Nigeria.* Solar & wind technology, 1986. **3**(2): p. 89-93.

9. Olatomiwa, L., et al., *Adaptive neuro-fuzzy approach for solar radiation prediction in Nigeria.* Renewable and Sustainable Energy Reviews, 2015. **51**: p. 1784-1791.
10. Olatomiwa, L., et al., *A support vector machine–firefly algorithm-based model for global solar radiation prediction.* Solar Energy, 2015. **115**: p. 632-644.
11. Bonissone, P.P., *Soft computing: the convergence of emerging reasoning technologies.* Soft computing, 1997. **1**(1): p. 6-18.
12. Wu, J., et al., *Prediction of solar radiation with genetic approach combing multi-model framework.* Renewable Energy, 2014. **66**: p. 132-139.
13. Landeras, G., et al., *Comparison of Gene Expression Programming with neuro-fuzzy and neural network computing techniques in estimating daily incoming solar radiation in the Basque Country (Northern Spain).* Energy Conversion and Management, 2012. **62**: p. 1-13.
14. Mohammadi, K., et al., *Support vector regression based prediction of global solar radiation on a horizontal surface.* Energy Conversion and Management, 2015. **91**: p. 433-441.
15. Mohammadi, K., et al., *A new hybrid support vector machine–wavelet transform approach for estimation of horizontal global solar radiation.* Energy Conversion and Management, 2015. **92**: p. 162-171.
16. Kocabaş, F. and Ş. Ülker, *Estimation of critical submergence for an intake in a stratified fluid media by neuro-fuzzy approach.* Environmental Fluid Mechanics, 2006. **6**(5): p. 489-500.
17. Benghanem, M., A. Mellit, and S. Alamri, *ANN-based modelling and estimation of daily global solar radiation data: A case study.* Energy conversion and management, 2009. **50**(7): p. 1644-1655.
18. Al-Alawi, S. and H. Al-Hinai, *An ANN-based approach for predicting global radiation in locations with no direct measurement instrumentation.* Renewable Energy, 1998. **14**(1-4): p. 199-204.
19. Jiang, Y., *Computation of monthly mean daily global solar radiation in China using artificial neural networks and comparison with other empirical models.* Energy, 2009. **34**(9): p. 1276-1283.
20. Mohandes, M.A., *Modeling global solar radiation using Particle Swarm Optimization (PSO).* Solar Energy, 2012. **86**(11): p. 3137-3145.
21. NIMET, *Nigerian Meteorological Agency, Kano, Kano State, Nigeria.* 2016.
22. NASA, *Surface meteorology and Solar Energy, https://eosweb.larc.nasa.gov/sse/.* 2016.
23. Izgi, E., et al., *Short–mid-term solar power prediction by using artificial neural networks.* Solar Energy, 2012. **86**(2): p. 725-733.
24. Schalkoff, R.J., *Artificial neural networks.* 1997: McGraw-Hill Higher Education.

APPENDIX A (Data set used for the prediction)

Year	Min. Temp	Max Temp	Sunshine	Humidity	Solar rad	Estimated
2003	13.1	30.7	10.1	25	18.324	18.64188
	17.4	34.5	12	28	21.456	21.36672
	19.8	35.6	10.1	17	23.148	22.83876
	25.3	40	7.5	41	22.572	22.33764
	24.4	39.3	7.3	41	22.464	22.24368
	22.8	33.3	7	70	19.692	19.83204
	21.8	31.3	6.7	77	17.388	17.82756
	21.2	30.5	7.5	81	15.876	16.51212
	21.9	31.8	8	77	18.576	18.86112
	22	35.8	8.5	59	20.592	20.61504
	11.9	34.2	9.3	33	21.96	21.8052
	13.6	29.5	8.1	35	20.052	20.14524
2004	14.4	30.2	8	20	18.9	19.143
	16	31.4	9.1	17	20.664	20.67768
	19.7	35	9.4	14	23.256	22.93272
	24.9	40.1	8.2	24	23.652	23.27724
	25	37.6	8.5	59	21.96	21.8052
	23.3	34	8	67	20.448	20.48976
	22	31	7.8	76	17.892	18.26604
	21.4	30.7	8	78	16.164	16.76268
	22.3	33.1	8.6	73	20.16	20.2392
	21.3	35.9	7.5	45	21.744	21.61728
	18	34.6	7.3	31	20.484	20.52108
	14.5	32.1	8.6	31	19.692	19.83204
2005	13.3	28.2	8.5	25	19.152	19.36224
	20.8	36.5	9.5	18	21.42	21.3354
	22.8	38.5	8.8	18	22.464	22.24368
	24.8	39.9	9	30	23.472	23.12064
	25.6	38.2	6.6	52	21.528	21.42936
	24.1	34.9	5	67	18.864	19.11168
	22.1	31	5.4	78	16.2	16.794
	21.9	29.9	5.8	82	14.904	15.66648
	22.4	33	8.7	72	20.88	20.8656
	20.6	33.9	7.9	55	20.736	20.74032
	16.3	33.6	8.8	24	20.628	20.64636
	15.1	30	9	23	20.088	20.17656

2006	16	27.8	8	22	19.512	19.67544
	19.4	36.2	8.4	23	21.996	21.83652
	20.5	37.1	7	15	22.536	22.30632
	23	39	9.1	26	24.912	24.37344
	25.2	36.7	8.4	59	20.664	20.67768
	24.4	35	6.1	64	21.456	21.36672
	23	32.9	6.4	72	19.368	19.55016
	22.1	30.5	5	79	14.416	15.24192
	22.1	31.6	7	77	18.54	18.8298
	21.9	34.4	8.6	59	21.312	21.24144
	16.4	31.7	8.6	34	20.376	20.42712
	13.2	28.1	8.1	53	19.44	19.6128
2007	12.5	27.1	5.6	46	19.836	19.95732
	16.6	34	8.8	30	21.204	21.14748
	20.3	35.8	7.9	24	23.004	22.71348
	25.7	39.5	7.9	47	22.536	22.30632
	25.9	37.3	7	62	20.952	20.92824
	22.6	33.5	3.2	71	20.34	20.3958
	22.6	31.7	3.2	75	19.044	19.26828
	22	30.1	2.6	81	17.28	17.7336
	22.4	32.7	4.5	71	21.312	21.24144
	21.1	36.3	9.4	48	23.364	23.02668
	18.5	34.7	4.9	27	21.924	21.77388
	14.7	31	4.5	33	20.772	20.77164
2008	12.8	26.7	4.9	32	21.672	21.55464
	14.3	29.3	3.9	23	24.084	23.65308
	21.1	38	8.2	23	25.56	24.9372
	23.5	38.5	7.9	28	24.804	24.27948
	25.4	38.4	8	50	22.428	22.21236
	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	22.1	31	7.2	78	19.728	19.86336
	22	30	6.5	81	18.216	18.54792
	22.3	32.3	7.6	77	20.664	20.67768
	21	34.4	8.8	48	22.104	21.93048
	16.6	33.6	9.6	27	21.708	21.58596
	15.6	31.7	8	31	20.376	20.42712
2009	15.6	31.8	8.4	25	21.276	21.21012
	18.4	34.8	8	7	23.616	23.24592
	20.6	37	7.8	18	25.452	24.84324
	26.1	39.7	8.5	44	24.3	23.841
	25.2	38	7.8	52	23.86	23.4582
	24.4	36.8	7.9	59	21.24	21.1788
	21.3	32.8	7.1	73	19.62	19.7694

	22.8	32.2	6.8	76	20.556	20.58372
	23.2	35.1	8.4	64	21.132	21.08484
	18.3	33.2	8.4	34	21.492	21.39804
	14.1	31.6	9.5	29	20.808	20.80296
2010	13.9	31.8	9.9	21	22.14	21.9618
	18.2	36	9.1	18	24.12	23.6844
	21.8	37.2	6.7	24	24.552	24.06024
	24.8	39.9	7.1	38	24.516	24.02892
	26.5	38.6	7	59	23.832	23.43384
	24.4	35.2	5.5	68	20.304	20.36448
	22.6	31.5	5.8	79	17.604	18.01548
	22.2	30.9	5.9	82	17.784	18.17208
	22.3	31.7	7.7	77	19.548	19.70676
	22.7	34.5	7.9	66	21.168	21.11616
	18.1	34.9	9.7	26	21.024	20.99088
	13.3	30.5	8.5	27	20.844	20.83428
2011	11.9	29	8.1	25	21.744	21.61728
	18.9	35.4	8.3	24	23.004	22.71348
	22	36.4	8.1	28	25.668	25.03116
	23.2	39.4	8.4	32	24.804	24.27948
	25.5	39.2	8.7	52	23.832	23.43384
	24	35	7.3	65	21.636	21.52332
	22.3	31.8	7.4	74	20.628	20.64636
	21.4	30.2	6.3	80	18.756	19.01772
	21.7	32.3	8	74	21.348	21.27276
	21.1	34.2	8.1	54	21.456	21.36672
	14.6	33.3	10.4	24	21.816	21.67992
	12	29	8.1	27	20.988	20.95956
2012	11.9	29.5	8.1	24	21.996	21.83652
	17.2	34.8	7.9	27	23.688	23.30856
	18.9	35.5	7	21	25.308	24.71796
	25.4	40.4	7.5	42	24.912	24.37344
	25.3	38.4	7.4	53	22.968	22.68216
	23	33.7	7	70	21.672	21.55464
	22.1	30.9	6.8	79	18.684	18.95508
	21.1	29.7	6.7	82	16.74	17.2638
	23.2	32.3	7.5	73	19.44	19.6128
	22.6	36.3	8.9	57	22.176	21.99312
	17	35	9.3	28	21.06	21.0222
	12.7	30.6	9	26	20.628	20.64636