PAPER • **OPEN ACCESS**

Forecasting of global solar radiation using anfis and armax techniques

To cite this article: Auwal Muhammad *et al* 2018 *IOP Conf. Ser.: Mater. Sci. Eng.* **303** 012016

IOP Conf. Series: Materials Science and Engineering **303** (2018) 012016 doi:10.1088/1757-899X/303/1/012016

Forecasting of global solar radiation using anfis and armax techniques

Auwal Muhammad[1, a], M. S. Gaya[2,b*], Rakiya Aliyu[1], Rabi'u Aliyu Abdulkadir[2], Ibrahim Dauda Umar[1], Lukuman Aminu Yusuf[3] and Mudassir Umar Ali[1],M.T.M Khairi[4]

[1]Department of Physics, Kano University of Science and Technology, Wudil, Nigeria
[2]Department of Electrical Engineering, Kano University of Science and Technology, Wudil, Nigeria
[3]Department of Electrical Engineering, Bayero University, Kano, Nigeria
[4]Deparment of Control & Mechatronics, Universiti Teknologi Malaysia, Malaysia

[a]auwalsafa@gmail.com, [b]muhdgayasani@gmail.com

Abstract. Procurement of measuring device, maintenance cost coupled with calibration of the instrument contributed to the difficulty in forecasting of global solar radiation in underdeveloped countries. Most of the available regressional and mathematical models do not capture well the behavior of the global solar radiation. This paper presents the comparison of Adaptive Neuro Fuzzy Inference System (ANFIS) and Autoregressive Moving Average with eXogenous term (ARMAX) in forecasting global solar radiation. Full-Scale (experimental) data of Nigerian metrological agency, Sultan Abubakar III international airport Sokoto was used to validate the models. The simulation results demonstrated that the ANFIS model having achieved MAPE of 5.34% outperformed the ARMAX model. The ANFIS could be a valuable tool for forecasting the global solar radiation.

1. Introduction

Global solar radiation refers to the rate of the algebraic sum of direct and diffuses incoming solar energy received at the earth's surface. Pyranometer is the most commonly used instrument to measure global solar radiation. Procurement of the pyranometer instrument, its maintenance cost together with calibration of the instrument made the forecasting of global solar radiation a quite difficult and challenging task.

Literature studies indicated that several models ranging from intelligent models to regressional models were developed. Regressional models such as ARMA and ARX belong to a family of linear models, commonly used in forecasting due to the capability of dealing with large data samples and may yield a better forecasting, but produce poor forecasting for few samples of data [1]. Intelligent models such as neural network [2], [3], [4] and Fuzzy logic are versatile, accurate and effective in handling noisy/ few samples data. However, choice of structure, trapping in local minima and selecting of membership function are the limitations of intelligent models.

A combination of neural network and fuzzy logic yielded a neuro-fuzzy which overcomes the limitations of the individual method. ANFIS belongs to a class of hybrid neuro-fuzzy and has received universal acceptability since evolution. ANFIS has an effective capability for nonlinear mapping. Linear models such as ARMAX are straightforward to implement and frequently used as a traditional tool for time-series forecasting [1]. ARMAX is an extension of ARX model and more versatile in handling disturbance modelling compared to ARX model. This paper centered on comparing ANFIS and ARMAX in forecasting the global solar radiation.

The forecasting performances of the models were evaluated using mean absolute percentage error (MAPE) and root mean square error (RMSE). Based on the judgement as reported in [5], model with MAPE less than or equal to 10% is considered highly accurate. The paper is organized as section 2 describes the study area, section 3 discusses ANFIS and ARMAX models while section 4 presents the simulation results and discussion.

2. Study Area

Nigeria is located in the equatorial region between latitudes 4oN and 14oN, longitudes 3oE and 15oE, the annual average daily sunshine ranges from about 3.5 hours at the coastal areas to about 9.0 hours at the far northern boundary, while the annual average daily solar radiation for the location is between 3.5 kWhm-2day-1 and 7.0 kWhm-2day-1 respectively [6]. Sokoto state is found in the North Western region of Nigeria, and is located in the sudano sahelian savanna ecological belt of Nigeria with longitude 11o3' to 13o50'E, latitude 4o to 6o40'. Sokoto falls within the hottest region in Nigeria. Therefore, the temperatures are of high extremes, with an average daily minimum of 16oC during cool months of January and December, and similarly in the hottest months of April to June, an average maximum of 38oC and minimum of 24oC [7, 8].

In this paper, meteorological data consisting of the monthly mean of global solar radiation, sunshine duration, maximum temperature, wind speed, rainfall, relative humidity and mean evaporation for a period of 10 years (2005-2014) for Sokoto, Northwestern Nigeria, with latitude of 12.55°N and longitude of 5.0°E were used. The data obtained from Nigerian Meteorological Agency, Sultan Abubakar III International Airport Sokoto, Sokoto State. The four parameters serve as input parameters for predicting solar radiation.

3. Methodology

ANFIS: ANFIS has an ability of fast learning, adaptability, effective handling of imprecision and uncertainty [9]. ANFIS is composed of nodes and five layers as illustrated in Fig. 1 below [10]. The square nodes are known as adaptive having parameters in them to be updated during learning process, and the circular nodes are fixed.

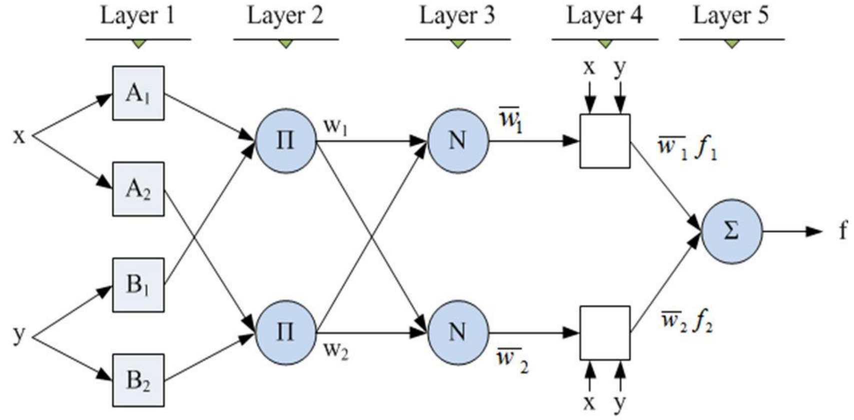

Figure 1. ANFIS structure

IOP Conf. Series: Materials Science and Engineering **303** (2018) 012016 doi:10.1088/1757-899X/303/1/012016

The structure of ANFIS is not unique, two or more layers could be combined together and produce same results [9]. The parameters of ANFIS are updated through supervise learning to reduce the error measure.

ANFIS Model: Since historical data may contain corrupted measurements, missing values, erroneous values and outliers. The data were treated in order to achieve reliable prediction. The data were selected randomly into training and testing data, 90% for training and 10% for testing. Two (2) Gaussian membership functions were assigned to each input, which generated sixty four (64) fuzzy rule. The structure of ANFIS is developed using MatLab command “genfis 1” to generate first- order Sugeno Fuzzy Inference System (FIS). As the structure is realized, the ANFIS uses hybrid learning algorithm to update the parameters of the FIS through learning from the data set to realize the target.

ARMAX: ARMAX is essentially a linear regression model that utilizes an auto regressive moving average type model for residuals. The following equation depicts the form of the ARMAX model:

$$A(q)y(t) = B(q)u(t-nk) + C(q)e(t) \quad (1)$$

Where $y(t)$ is the system is outputs; $u(t)$ is the system inputs, **Error! Bookmark not defined.** is the system delay and $e(t)$ is the system disturbance. $A(q)$, $B(q)$ and $C(q)$ are polynomial with respect to the backward shift operator q.

ARMAX Model. The same treated data used for developing ANFIS model were utilized for realizing ARMAX model and with 90% of the data for training and 10% for testing. The structure of the model was selected with na, nb, nc and nk equal 2 [2 2 2 2 2 2] 2 [1 1 1 1 1 1] and the prediction error method was utilized for the forecasting.

4. Results and Discussions

The Fig. 2 and Fig 3. demonstrated the inputs which include relative humidity (RH), rainfall (RF), maximum temperature (Max T), wind speed (WS), sun shine hours (SSH) and mean evaporation (MEV).

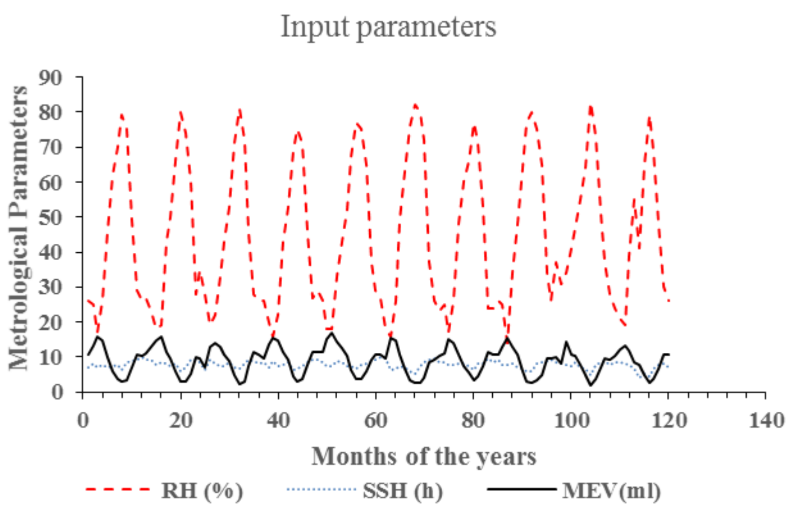

Figure 2. Input metrological parameters

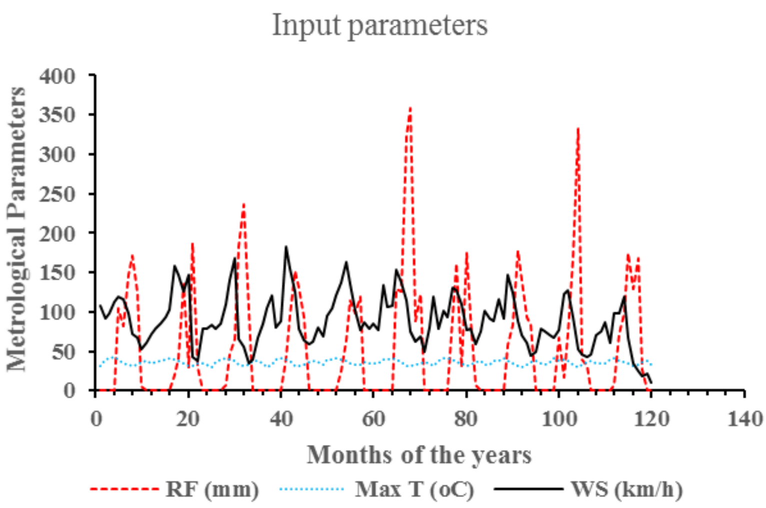

Figure 3. Input metrological parameters

The commonly available model evaluation criteria such as root mean square error (RMSE) and mean absolute percentage error (MAPE) were used measure the forecasting performances of the models.

$$MAPE = \frac{100\%}{N} * \sum_{i=1}^{N} \left| \frac{x_i - y_i}{x_i} \right| \quad (2)$$

$$RMSE = \sqrt{\frac{\sum (x_i - y_i)^2}{N}} \quad (3)$$

Where x_i depicts measured value, y_i is the forecast value, and N is the number of samples.

The Fig. 4 and Fig. 5 illustrate the forecasting performances of the model during the training and testing respectively. The Table 1 presents the results obtained during the training and testing.

Table1: Model Performance

Model	Training		Testing	
	MAPE (%)	RMSE	MAPE (%)	RMSE
ANFIS	0.002	0.001	5.340	0.562
ARMAX	45.981	2.717	41.063	2.586

It is apparent from the Fig. 4 during the training phase that the ANFIS model outperformed the ARMAX in forecasting having tracked well the pattern of the measured global solar radiation and achieved the MAPE of 0.002%, thus indicating a highly accurate forecasting.

Similarly, during testing as shown in Fig. 5, the ANFIS model predicted well the measured global solar radiation having achieved the MAPE of 5.340%, which is also highly accurate forecasting. The performances of ARMAX in both training and testing are below expectation as compared to that of ANFIS model.

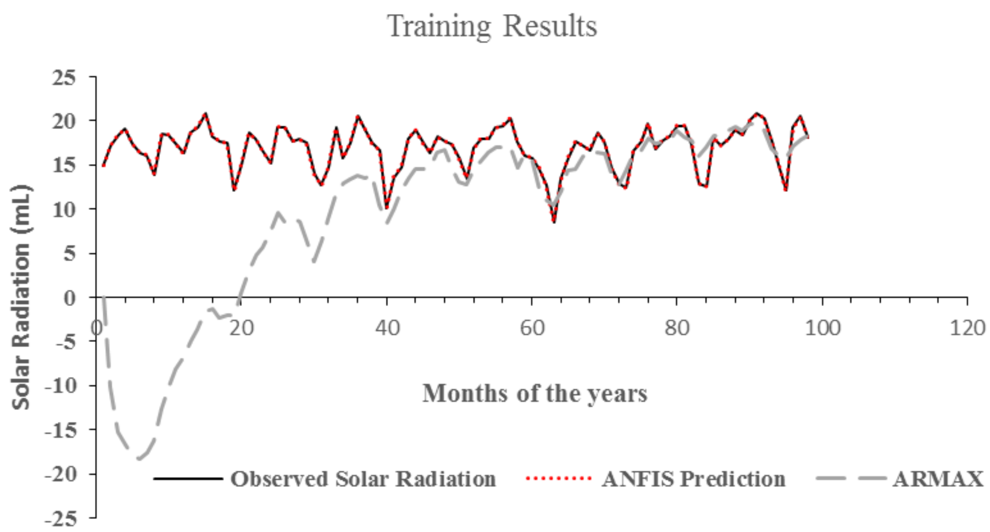

Figure 4. Models forecasting performance during training

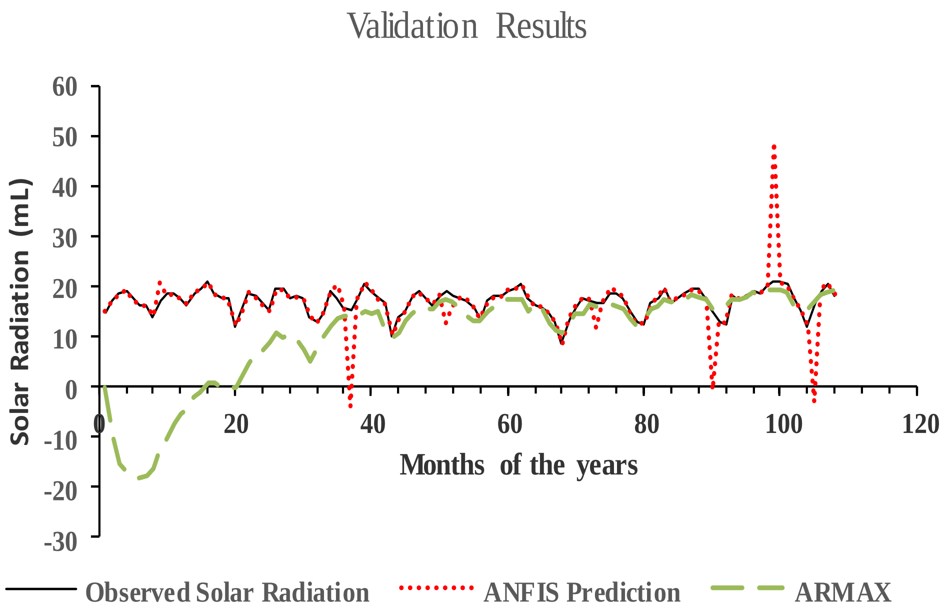

Figure 5. Models forecasting performance during testing

5. Conclusion

The paper has presented an ANFIS and ARMAX techniques in forecasting global solar radiation. The results obtained demonstrated the ANFIS performed far better than the ARMAX model having achieved the MAPE of less than 10% in both training and testing. Increasing the order of the ARMAX may enhance the performance of the model. However computational burden needs to be avoided. The ANFIS model would serve as a useful forecasting tool for the global solar radiation in the study area and those with similar geographical information.

IOP Conf. Series: Materials Science and Engineering **303** (2018) 012016 doi:10.1088/1757-899X/303/1/012016

References

[1] M. S. Gaya, N. Abdulwahab, Y. M. Sam, S. I. Samsudin, and I. W. Jamaludin: Applied mechanics and Materials Vol. 554 (2014), p. 360-365

[2] M. Benghanem, A. Mellit, and S. N. Alamri: Energy conversion and Management Vol. 50 (2009), p. 1644-1655

[3] A. Hasni, A. Sehli, B. Braoui, A. Bassou, and B. Mieur: Energy Procedia Vol.18 (2012), p. 531-537

[4] J. Mubiru and E. J. K. B. Banda: Solar energy Vol. 82 (2008), p. 181-187

[5] K. D. Lawrence, R. K. Klimberg and S. M Lawrence: *Fundamental of Forecasting using Excel* (Industrial Press Inc., New York 2009)

[6] S. Salisu, B. O. Sadiq, A. S. Abubakar, Y. Jibril and S. Garba: International Journal of Scientific and Engineering Research Vol. 5 (2014), p. 669-675

[7] S. A. Abdullahi, M. M. Mohammed, B. K. Adeoyun, and I. U. Mohammed: Resources and Enviroment Vol. 4 (2014), p. 220-233

[8] G. Atedhor: African Journal of Food Agriculture, Nutrition and Development Vol. 15 (2015), p. 9856-9871

[9] M.S Gaya: *Neuro-Fuzzy Modelling and Neural Network Internal Control of an Activated* Sludge *System* (Universiti Teknologi Malaysia PhD Thesis 2014)

[10] J. S. R. Jang: IEEE transactions on system, man and cybernetics Vol. 23 (1993), p. 665-668