Nigerian Journal of Technology (NIJOTECH)
Vol. 42, No. 1, March, 2023, pp.64 - 71
www.nijotech.com

Print ISSN: 0331-8443
Electronic ISSN: 2467-8821
https://doi.org/10.4314/njt.v42i1.8

NEURAL-NETWORK MODELING OF SOLAR RADIATION AND TEMPERATURE VARIABILITY DUE TO CLIMATE CHANGE IN IBADAN METROPOLIS

A. O. David[1,*], A. O. Oyedeji[2], O. T. Opafola[1], and A. J. Ogunjimi[1]

[1]Department of Civil Engineering, Olabisi Onabanjo University, Ago-Iwoye, Ogun State, Nigeria.
[2]Department of Computer Engineering, Olabisi Onabanjo University, Ago-Iwoye, Ogun State, Nigeria.

*corresponding author (Phone Number: +234-803-336-5945. Email: adekunle.david@oouagoiwoye.edu.ng)

Article history: Received 12 October, 2022. Revised 11 February, 2023. Accepted 04 March, 2023

Abstract
This research focused on studying the variability of solar radiation and temperature under climate change in the Ibadan metropolis. In the study, spatial distribution, temporal variations, annual distribution, estimation and prediction of the solar radiation, minimum and maximum temperature data in the Ibadan Metropolis was collected. A Long Short-Term Memory Neural Network (LSTM-NN) model was developed for the prediction using the time-series data obtained. An ARIMA model was further developed to compare and validate the LSTM-NN model. The performance of the prediction models were determined using the root mean square error (RMSE) and the mean absolute percentage error (MAPE). The RMSE values for the minimum, maximum temperature and solar radiation predictions were 1.543, 1.290, 1.967, and 1.611, 1.309, 2.106 for the LSTM-NN and ARIMA models respectively, while the MAPE values for the minimum, maximum temperature and solar radiation predictions were 3.603, 4.351, 8.859, and 3.840, 4.480, 9.502 for the LSTM-NN and ARIMA models respectively. The LSTM-NN model had a better prediction performance in all categories with lower error when compared with ARIMA. From the prediction, it was observed that there will be a reduction in the maximum temperature, minimum temperature and solar radiation values when compared to obtained data. The observed minimum temperature ranged from 22.9032-23.2032(^0C), while the predicted minimum temperature ranged from 19.9260-19.977(^0C) also the observed maximum temperature ranged from 32.87096-33.7064(^0C), while the predicted maximum temperature ranged from 29.5159-29.5529(^0C), the observed solar radiation ranged from 19.203-19.722 (W/m^2), while the predicted solar radiation ranged from 14.123-14.115 (W/m^2). The year with the highest solar radiation which constitutes the useful energy is 2024 with an average value of 14.1395 W/m^2.

Keywords: : Solar Radiation, Temperature, Climate Change, Long Short-Time Memory Neural Network Model.

1.0 INTRODUCTION
The global climate change situation is becoming more severe due to the use of fossil energy, so the application of renewable energy sources has been receiving more attention. Renewable energy, often known as clean energy, is derived from renewable natural resources or processes. For instance, even if their availability is dependent on the time and weather, sunlight and wind continue to shine and blow [1]. According to the World Meteorological Organization (WMO), the classical period for describing climate is 30 years. A location`s climatic condition is affected by its latitude, terrain, altitude and the nearby water bodies with their currents. The climate of a region is ultimately determined by the radiation energy of the sun, and its distribution and temporal fluctuations [2]. Climate change refers to some observable variations in the climate system that are attributable to human (anthropogenic) activities, especially those that alter the atmospheric composition of the earth and ultimately lead to global warming [3]. Climate change has been observed to affect weather parameters (wind speed, solar radiation, precipitation, mean temperature, maximum and minimum temperatures etc.) that constitute renewable resources. [4].

The genesis and evolution of Earth's climate are largely regulated by the global energy balance and its spatial and temporal variations [5]. The basic global energy balance of the earth is between the energy coming from the Sun and the energy returned to space by the earth`s radiative emission. The sun which is a major source of renewable energy during the dry season is an atomic power from which energy can be controlled and exported to do useful work as a result of a high rate of 3.8×10^{23} kW. Global solar radiation coming from the sun through the atmosphere accounts immeasurably for the radiation incident on the earth’s surface. However, some interceptions and absorptions take place after the emission of solar radiation and due to this, only half of the emitted solar radiation reaches the earth's surface [6].

Solar radiation and temperature are relative where a change in solar radiation leads to a change in temperature and this is evident in the 30 years of data generated for the Ibadan metropolis from the Nigeria Meteorological Agency. In the data, it was observed that an increase in solar radiation led to an increase in temperature. The energy reaching the Earth’s surface in the form of direct or scattered radiation determines the temperature of both the surface of the earth and the lower atmosphere of the earth which in turn, determines the evaporation capacity and climatic features [7]. The temperature of the atmosphere increases rapidly above about 100km because of the heating produced by the absorption of ultraviolet radiation from the sun which dissolves oxygen and nitrogen molecules and ionizes atmospheric gases in the atmosphere [8].

Radiation is derived by the atmosphere through radioactive after it has been absorbed from the sun which falls on the earth's surface, thereby leading to different climate variations in Nigeria. If we wish to have a sustainable society built on sustainable energy resources, governments and businesses need to take direct and immediate action on climate change by militating against it. This can be done by investing in low-carbon energy, taxing carbon emissions, higher efficiency standards, reforestation and individual action to help reduce it. Global solar radiation from the sun which causes solar radiation and temperature can also be converted to renewable energy which can serve as an alternative fuel e.g., solar energy.

With enormous solar potential across Nigeria, a moderate seasonal effect of climate change can have significant socio-economic impacts; change of solar radiation in future climate is thus of considerable interest [9]. The intensity of solar radiation per day is usually one of the variables collected by meteorological stations in tropical Africa, Nigeria especially. These stations are limited in number due to the cost involved in establishing and maintaining them. This limits the availability of data to a few locations [10]. The artificial neural network (ANN) is one of the choices in the broad solar forecasting literature. ANN techniques for estimating irradiation have been shown to have greater accuracy than other techniques such as linear, nonlinear and fuzzy approaches [11], there is an increasing need for more precise and applicable modelling, forecasting and prediction of solar irradiance.

According to [12] Long Short-Term Memory (LSTM) is a novel recurrent network architecture in conjunction with an appropriate gradient-based learning algorithm. LSTMs are a type of Recurrent Neural Network (RNN) that can learn and memorize long-term dependencies. Recalling past information for long periods is the default behaviour. They are useful in time series prediction due to their ability to retain information over time and remember past inputs. LSTMs have an edge over conventional feed-forward neural networks and RNNs in many ways. This is because of their property of selectively remembering patterns for long durations of time. The LSTM network consists of the forget gate, input gate and output gate. The forget gate is responsible for removing information from the cell state, and the input gate is responsible for the addition of information to the cell state and The output gate determines the value of the next hidden state. The available computational models include linear regression models; satellite data-based models and Neural Network models using meteorological parameters.

2.0 MATERIALS AND METHOD

2.1 Materials

2.1.1 Data preparation

30 years of Solar radiation, minimum temperature and maximum temperature data from 1981-2010 were obtained from NIMET in Ibadan for this research. The data were then sorted into categories using Microsoft Excel for accuracy in the prediction.

2.2 Method

2.2.1 Data analysis

The analysis of the data was done using a Microsoft Excel Spreadsheet and a python notebook to generate charts for the mean monthly data of the minimum temperature and Solar Radiation and maximum temperature and Solar Radiation. This also involves the extraction, sorting and merging of the data that were collected to make them ready and suitable for entry into the network. In addition, the training data were scaled or transformed using the MinMaxScaler, where the minimum of the feature is made equal to zero and the maximum equal to one. This shrinks the data within the range of 0 to 1. The code snippet for the data transformation in python is shown in Figure 1.

The design of the LSTM-NN Model involved 5 processes which are:

1. Defining the Networks
2. Compiling the Network
3. Training the Network
4. Evaluating the network
5. Using the Network (Making Predictions)

```
print(train.shape)
print(test.shape)

(8765, 1)
(2192, 1)

[ ] # Normalize the data
    scalar = MinMaxScaler(feature_range=(0, 1))
    scaled_data = scalar.fit_transform(solar)

[ ] #Spilt data into x_train and y_train
    x_train, y_train = [], []
    for i in range(60, len(train)):
      x_train.append(scaled_data[i-60:i,0])
      y_train.append(scaled_data[i,0])

    x_train, y_train = np.array(x_train), np.array(y_train)

[ ] # now we have reshape the array to 3-d to pass the data into lstm [number of samples, time steps/batch_size, features]
    x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))

[ ] x_train.shape

    (8705, 60, 1)
```

Figure 1: Trained Data

The LSTM network consists of the forget gate, input gate and output gate as shown in Figure 2. Gates in LSTM are sigmoid activation functions i.e. they output a value between 0 and 1, which helps the network to update or forget the data. The forget gate is responsible for deciding which information needs attention and which can be ignored in the cell state while the input gate is used to quantify the importance of the new information carried by the input and the output gate determines the value of the next hidden state. The formulars for the forget, input and output gates are presented in equations 1-3 respectively.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (2)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (3)$$

Where f_t, i_t and o_t are the forget, input and output gates respectively, σ is the sigmoid function, W_x is the weight of the respective x gate neurons, h_{t-1} is output of the previous hidden state and $b_x$are the biases for the respective gates (x).

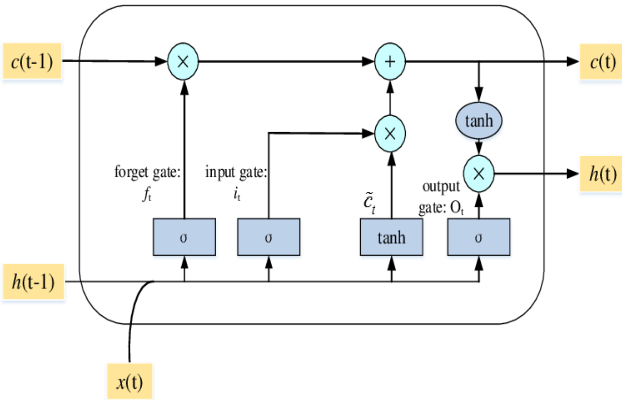

Figure 2: Architecture of the LSTM model

2.2.2 Analysis of predicted data

This involves the analysis of the predicted data using the Excel spreadsheet package and also Python notebook to study the resulting relationship between solar radiation and temperature and also determine the period with the useful energy.

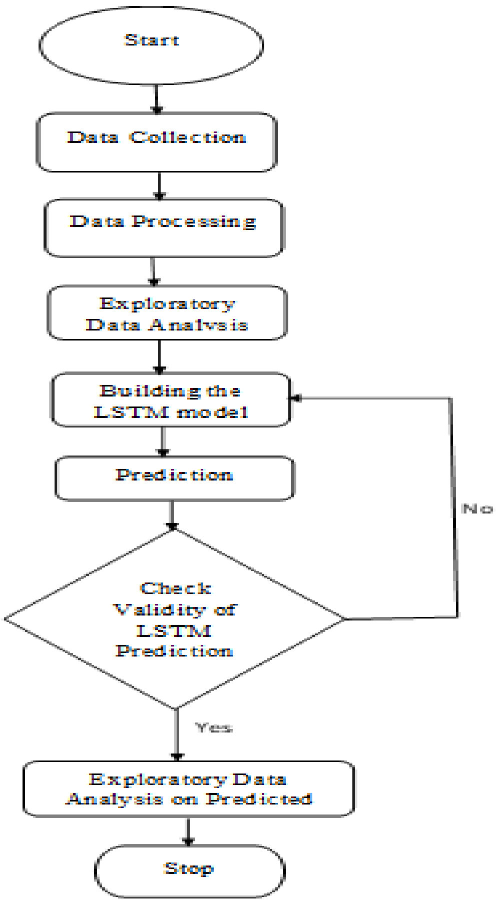

Figure 3: Process flowchart

The processes involved in this research from data collection and preprocessing, to model building and evaluation are presented in the process flowchart of Figure 3.

3.0 RESULTS AND DISCUSSIONS

3.1 Minimum Temperature Predictions

The Minimum temperature from 2011-2025 was first predicted by the LSTM. To test the performance of the network, the data was divided into two for each data set 1980-2005 and 2005-2010. The 1980-2005 data sets were used to predict the 2005-2010 data sets. Then predicted results were compared with the existing results and the results were close. The observation Figure 4 indicates a strong correlation between the observed and the predicted values which gives the go-ahead for future prediction.

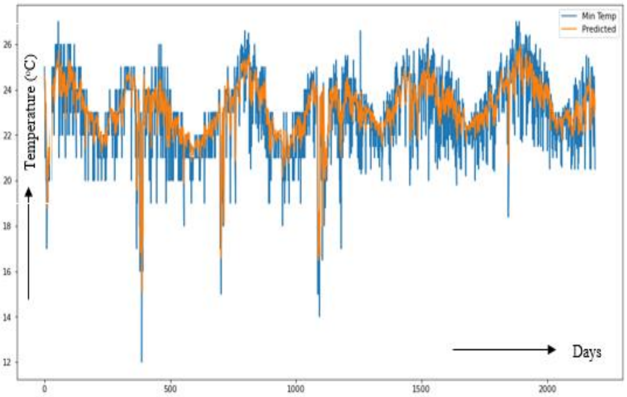

Figure 4: 2005-2010 predicted and observed data

Figure 5 shows the future prediction data chart from 2011-2025. It was observed in the chart that there will be a drastic decrease in the minimum temperature but there will be consistency compared to the existing data from 1980-2010.

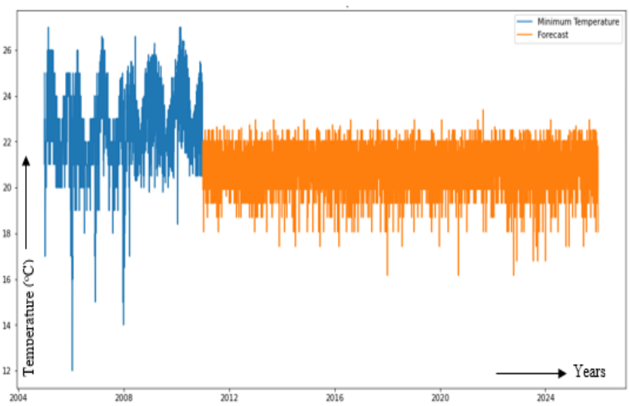

Figure 5: Minimum temperature future Prediction from 2011-2025

3.2 Maximum Temperature Predictions

The Maximum temperature from 2011-2025 was first predicted by the LSTM-NN. To test the performance of the network, the data was divided into two for each data set 1980-2005 and 2005-2010. The 1980-2005 data sets were used to predict the 2005-2010 data sets. Then predicted results were compared with the existing results and the results were close. Figure 6 shows the existing data being compared with the existing data. From the comparison, it was observed that the network was able to give a correlating trend between the observed and predicted data trend which gives the go-ahead for future prediction.

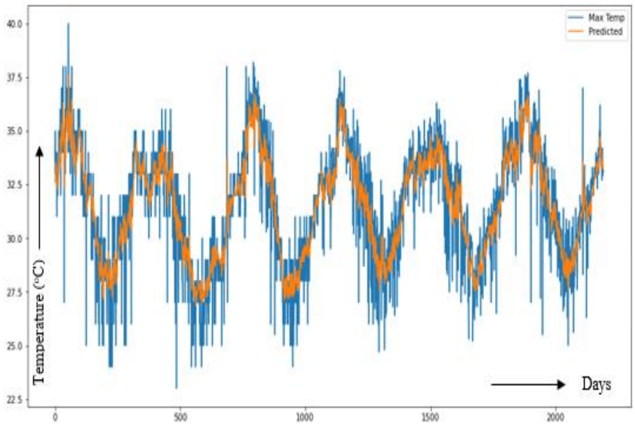

Figure 6: 2005-2010 predicted and observed data

Figure 7 shows the future prediction data chart from 2011-2025. It was observed in the chart that there will be a drastic decrease in the maximum temperature but there will be consistency compared to the existing data from 1980-2010.

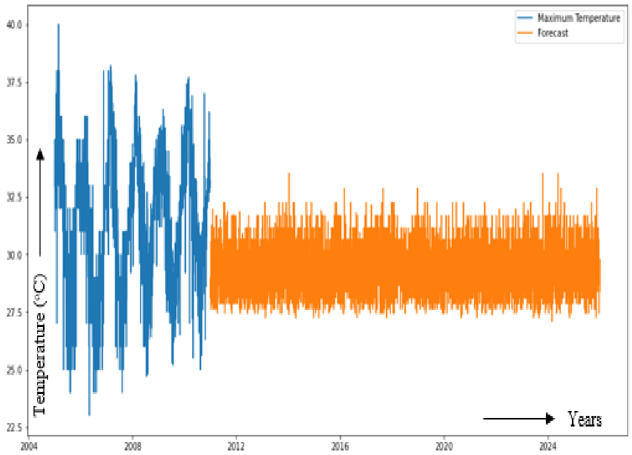

Figure 7: Maximum Temperature future projection from 2011-2025

3.3 Solar Radiation Predictions

Solar Radiation from 2011-2025 was first predicted by the LSTM-NN. To test the performance of the network, the data was divided into two for each data set 1980-2005 and 2005-2010. The 1980-2005 data sets were used to predict the 2005-2010 data sets.

Then predicted results were compared with the existing results and the results were close. Figure 8 shows the observed data is compared with the existing data.

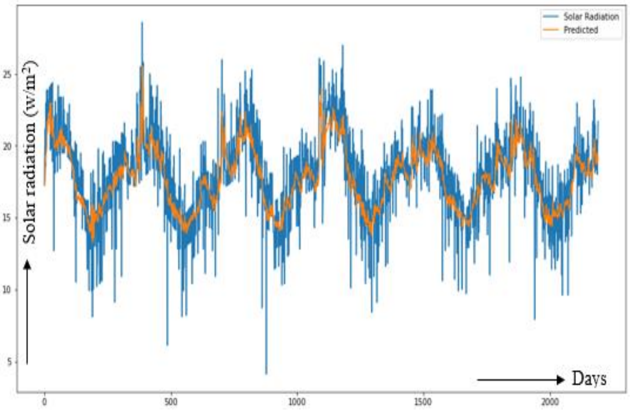

Figure 8: 2005-2010 predicted and observed data

From the chart above, it was observed that the model was able to predict the existing data almost correctly which gives a go-ahead for future predictions. Figure 9 below shows the future projection from 2011-2025.

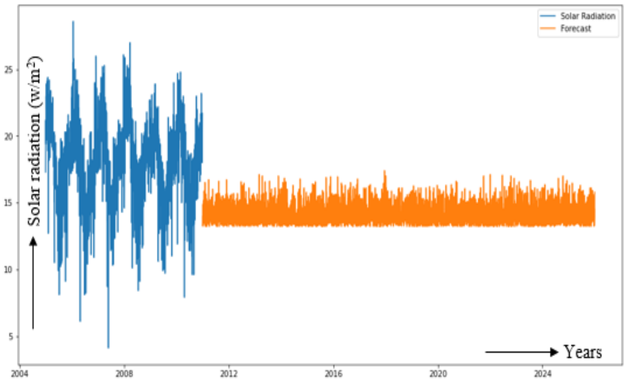

Figure 9: Solar Radiation future projection from 2011-2025

From the Chart in Figure 9, it was predicted that there will be a sharp decrease in the solar radiation data after 2010.

3.4 Validation of the Result

The predicted results were validated by running a prediction with an ARIMA model and then comparing the root mean square error and mean absolute error of the ARIMA and the LSTM-NN predictions. Figure 10 below shows the comparison between the Predictions done by the ARIMA model for minimum temperature.

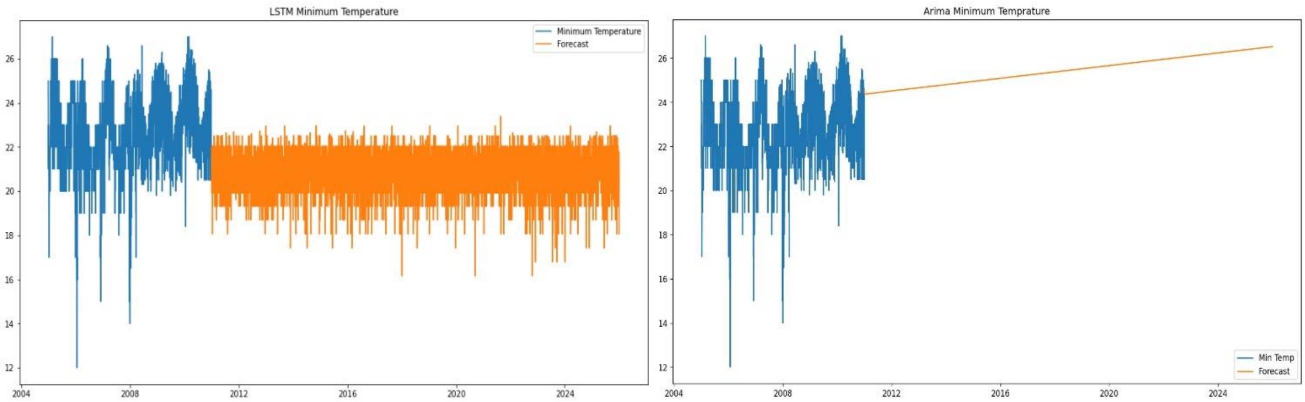

Figure 10: Comparison between the ARIMA model and LSTMM min. temperature predictions

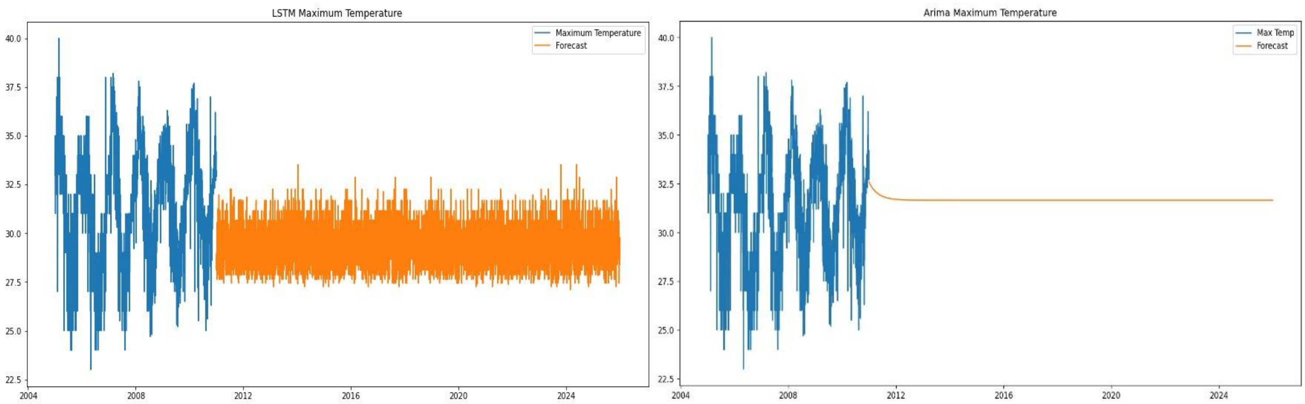

Figure 11: Comparison between the Arima and LSTM Prediction for Maximum Temperature

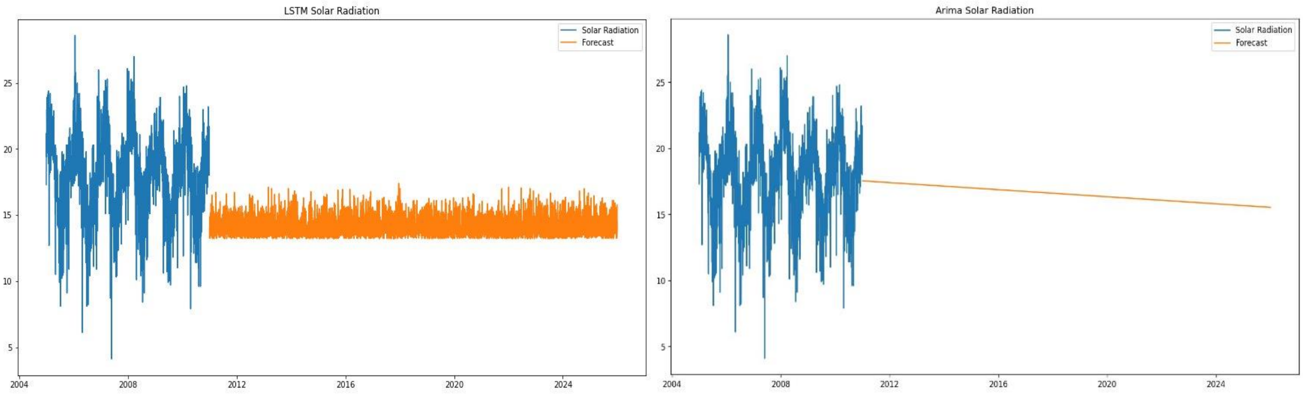

Figure 12: Comparison between the ARIMA and LSTM prediction for Solar Radiation.

Figure 10 shows that the LSTM and the ARIMA prediction are so different; the LSTM predicted a wavy trend while the ARIMA predicted an upward trend. Figure 11 indicates that the ARIMA predicted more of a uniform trend compared to the wavy trend predicted by the LSTM. Figure 12 above shows that the ARIMA model predicted a continuous downward trend for Solar Radiation which is different from the wavy-like trend the LSTM model predicted a wavy trend.

3.5 Root Mean Square Error and Mean Absolute Error Values

The root mean square error (RMSE) and the mean absolute percentage error (MAPE) values which were used for validation of predicted results were calculated by the models. The RMSE is the standard deviation of the residuals that is the prediction errors while the MAPE measures the accuracy of a forecast system as a percentage. The formulas for the RMSE and the MAPE are given in equations 4 and 5 respectively.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \quad (4)$$

$$MAE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \quad (5)$$

Where $\hat{y}_i$ is the predicted or forecast value; y_i is the actual value; n is number of fitted points.

Table 1 shows the RMSE and MAPE for both the ARIMA and LSTM models for Minimum temperature, maximum temperature and Solar Radiation.

Table 1: The RMSE and MAPE values for ARIMA and LSTM models.

	RMSE			MAPE		
MODELS	MAX. TEMP	MIN. TEMP	SOLAR RAD.	MAX. TEMP	MIN. TEMP	SOLAR RAD.
ARIMA	1.611	1.309	2.106	3.840	4.480	9.502
LSTM-NN	1.543	1.230	1.967	3.603	4.351	8.859

Table 1 above shows that the LSTM root mean square values and Mean absolute percentage error values are closer to 1 compared to the ARIMA root mean square values. Hence this validates the results provided by the LSTM model.

3.6 Relationship Between Solar Radiation and Temperature

The relationship between the predicted Solar radiation, maximum temperature and minimum temperature data is being studied by analysing them into Charts whereby the Solar radiation and Minimum temperature are plotted in one Chart and the Solar Radiation and Maximum temperature are plotted in the other chart. The chart involves the yearly average of the various datasets.

Figure 13 below shows the Chart of observed Mean yearly Minimum temperature and mean yearly solar radiation. Figure 14 shows the Chart of predicted Mean yearly Minimum temperature and mean yearly solar radiation.

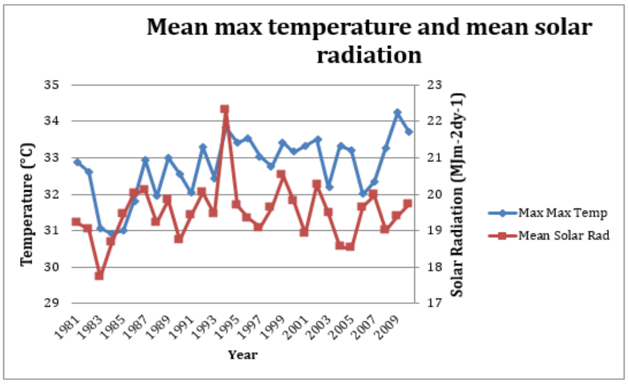

Figure 13: Observed Mean Minimum Temperature and Mean Solar Radiation.

From Figure 13 and Figure 14, it was observed that the mean minimum temperature and the mean solar radiation started from a rising position from the observed data and this is also true for the predicted data, in 1983 (for observed data) and 2012 (for the predicted data) sharp deep was noticed for the mean solar radiation which later moved up in 1984 and 2013 respectively, the mean min temperature falls gradually till 1986 (for the observed) when it gradually rose again but the mean min temperature for the predicted acted opposite by staying almost steady while the mean solar radiation fluctuated all through until 2019 when it was observed to go through a sharp fall and rose back to its almost steady position till 2025.

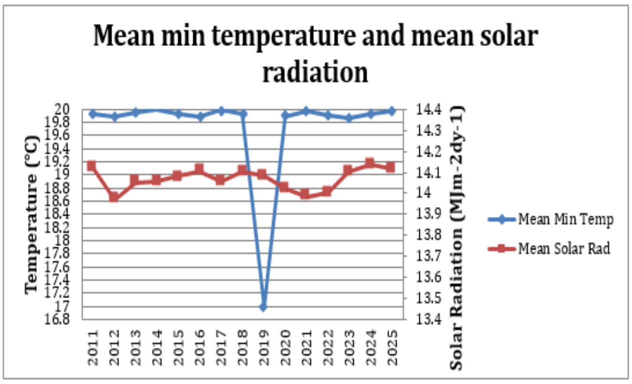

Figure 14: Predicted Mean Minimum Temperature and Mean Solar Radiation.

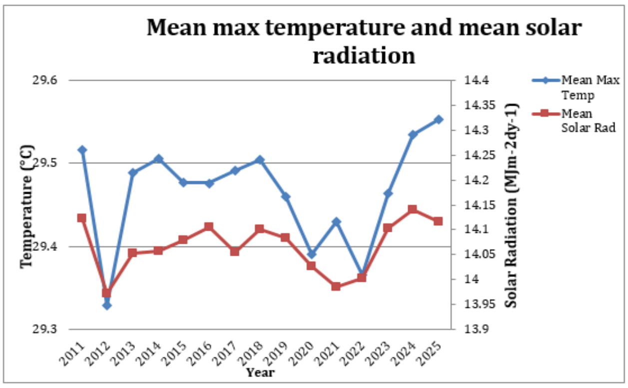

Figure 15: Observed Mean Maximum Temperature and Mean Solar Radiation.

It was observed generally that (for observed data) the mean min temperature and the mean solar radiation were inversely proportional to each other although when one is seen going up the graph the other is going down the graph and this is also validated in the year 1994 where the mean min temperature dipped sharply down the graph, the mean solar radiation, on the other hand, was observed to attain its peak by going sharp up the graph. While it was observed generally that (for the predicted data)the mean min temperature and mean solar radiation behaved almost directly proportional to each other and this is validated although the graph except for an exception in 2019 where the mean min temperature is seen to dip sharply while mean solar radiation is seen to stay on its flow.

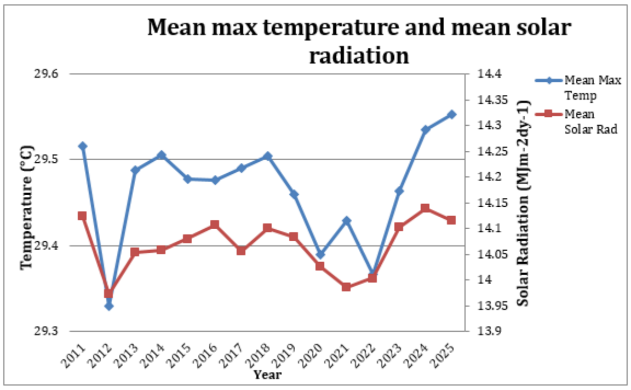

Figure 16: Predicted Mean Maximum Temperature and Mean Solar Radiation.

From Figures 15 and 16, it was observed that the mean maximum temperature and the mean solar radiation started from a rising position also from the observed data and this is also applicable to the predicted data, in 1983 (for observed data) there was a sharp dip in and mean solar radiation and it moved gradually up the graph again from 1984 until 1988 when it dipped a little again, but a gradual dip was noticed for mean max temperature in 1984 and it also gradually moved back up the graph from 1985 until it experienced a dip again in 1988 also. And 2012 (for the predicted data) sharp deep was noticed for the mean max temperature and the mean solar radiation 2012 and they both maintained almost a steady flow until there was a break in the flow in 2018 and 2017 respectively.

Generally, it was observed that (for the observed data) the mean min temperature and mean solar radiation behaved slightly directly proportional to each other and this is validated although the graph except for an exception in (1989-1990), (2004-2005) and (2007-2009). While (for observed data) the mean min temperature and the mean solar radiation were observed to be inversely proportional to each other although the graph except for 2012 when they both have a sharp dip as discussed earlier.

The Charts in Figure 14 and 16 indicates that the year 2024 is the year with the obtainable useful energy from Solar Radiation.

From the chart in Figure 9, it was discovered that the Maximum solar radiation is 18.03069 and it occurred on the 17th of December, 2017 but for future projections from the time of writing (2021-2025) the maximum solar radiation will be 17.68225 and it occurred on the 4th of January, 2022.

4.0 CONCLUSION

Temporal variations, annual distribution, estimation and prediction of solar radiations, minimum temperature and maximum temperature were carried out in this study using Long Short Term memory-Neural Network. Solar radiation, minimum temperature and maximum temperature data over the years (1981-2010) belonging to the Ibadan metropolis in Nigeria were divided into three portions (training, testing and validation) during the applications of a neural network model. The results of the validation and comparative study of the estimated and observed indicate that the Neural Network based estimation technique for solar radiation, minimum temperature and maximum temperature can be used to predict solar radiation, minimum temperature and maximum temperature as an alternative in areas where in situ measurement cannot be possible in Nigeria. This study also confirms the ability of the LSTM-NN models to predict solar radiation values precisely. The comparison results indicate that the LSTM-NN model is promising for evaluating the global solar radiation resource potential at places where there are no monitoring stations in Nigeria.

The study on the relationship between solar radiation and temperature indicates that there is a relationship between solar radiation and temperature. Therefore any change in the temperature will affect solar radiation.

REFERENCES

[1] (https://www.nrdc.org/stories/renewable -energy-clean-facts#sec-whatis)

[2] Balasubramanian A. “Elements of Climate and Weather”, *Publication of the Centre for Advanced Studies in Earth Science*, 1-19, 2017.

[3] Idowu, A. A., Ayoola, S. O., Opele, A. I., and Ikenweiwe, N. B. “Impact of Climate Change in Nigeria”, *Iranica Journal of Energy and Environment*. 2(2), 145-152, 2014.

[4] Li, D. H. W., Yang, L., Lam, J. C. “Impact of climate change on energy use in the built environment in different climate zones: A review”, *Energy*, 42 (1), 103–112, 2012.

[5] Wild, M., Folini, D., Schär, C., Loeb, N., Dutton, E., and König, L. G., Konig, L. “The global energy balance from a surface perspective. Climate Dynamics”, 40(11-12), 3107-3134, 2013.

[6] Ibeh, G. F., Bernadette, C. U., Tertsea, I., Tyovenda, A. and Ofoma, J. N. “Application of artificial neural networks for Global solar radiation forecasting With Temperature”. *IJECC*, 9(7), 376-390, 2012.

[7] Manual for Statistics on Energy Consumption in households. Publications office of the European Union, 2013. DOI: 10.2785/45686.

[8] Kpeglo, D. K. “The Relationship Between Incoming Solar Radiation And Daily Air Temperature”, Accra, Ghana: *University of Ghana*, 2013.

[9] Pan, Z., Segal, M., Arritt, R.W., Takle, E.S. “On the potential change in solar radiation over the US due to increases of atmospheric greenhouse gases. Renewable Energy”, 29, 1923–1928, 2004.

[10] Osinowo, A., Okogbue, E., Ogungbenro, S. B., and Olugbenga, F. “Analysis of Global Solar Irradiance over Climatic Zones in Nigeria for Solar Energy Applications”, *Journal of Solar Energy*, 2015, 1-9, 2015.

[11] Yadav, A. K., and Chandel, S. S. “Solar Radiation prediction using Artificial Neural Network techniques: A review”, *Renewable and Sustainable Energy Reviews*, 33, 772-781, 2014.

[12] Hochreiter, S. and Schmidhuber, J. “Long Short-Term Memory”, Neural Computation, 9, 1735-1780, 1997; https://doi.org/10.1162/neco.1997.9.8.1735